

BRAVE : Broadening the visual encoding of vision-language models

Oğuzhan Fatih Kar Alessio Tonioni Petra Poklukar

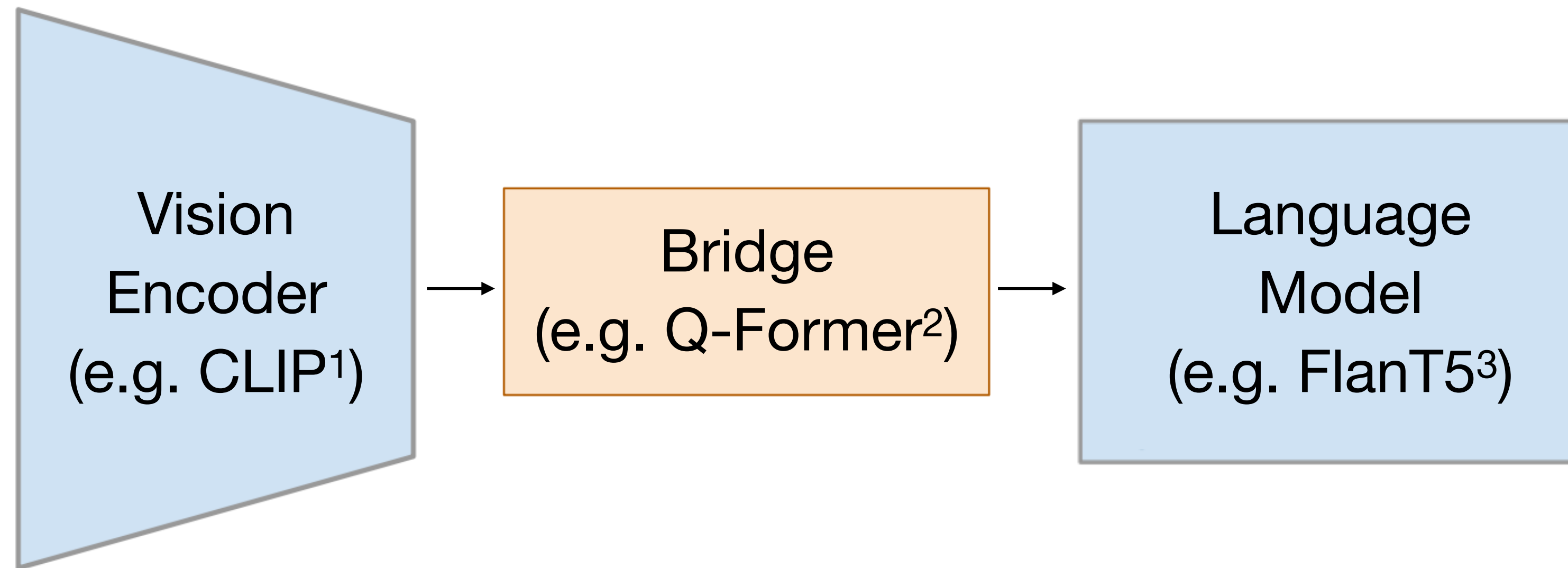
Achin Kulshrestha Amir Zamir Federico Tombari

ECCV 2024 (Oral)

brave-vlms.epfl.ch



Vision-Language Models (VLMs)



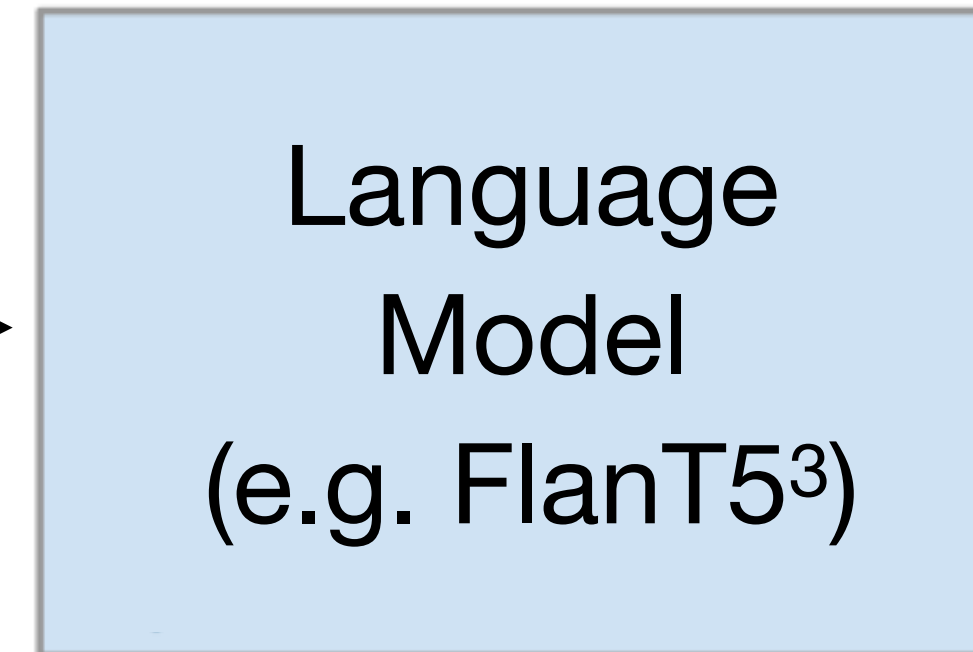
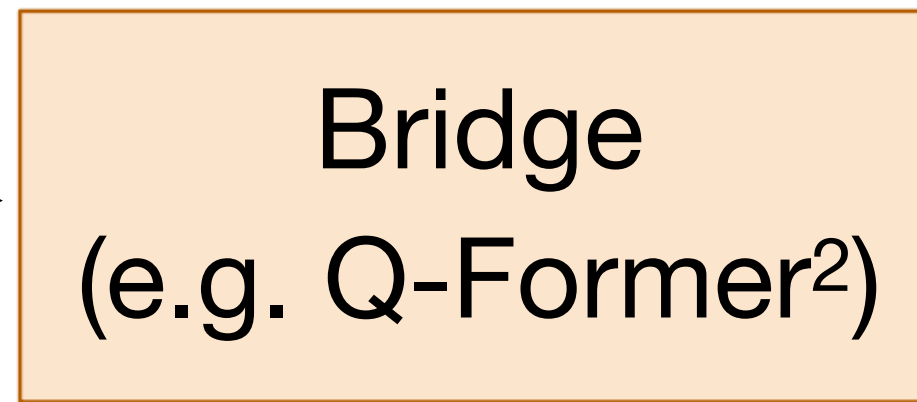
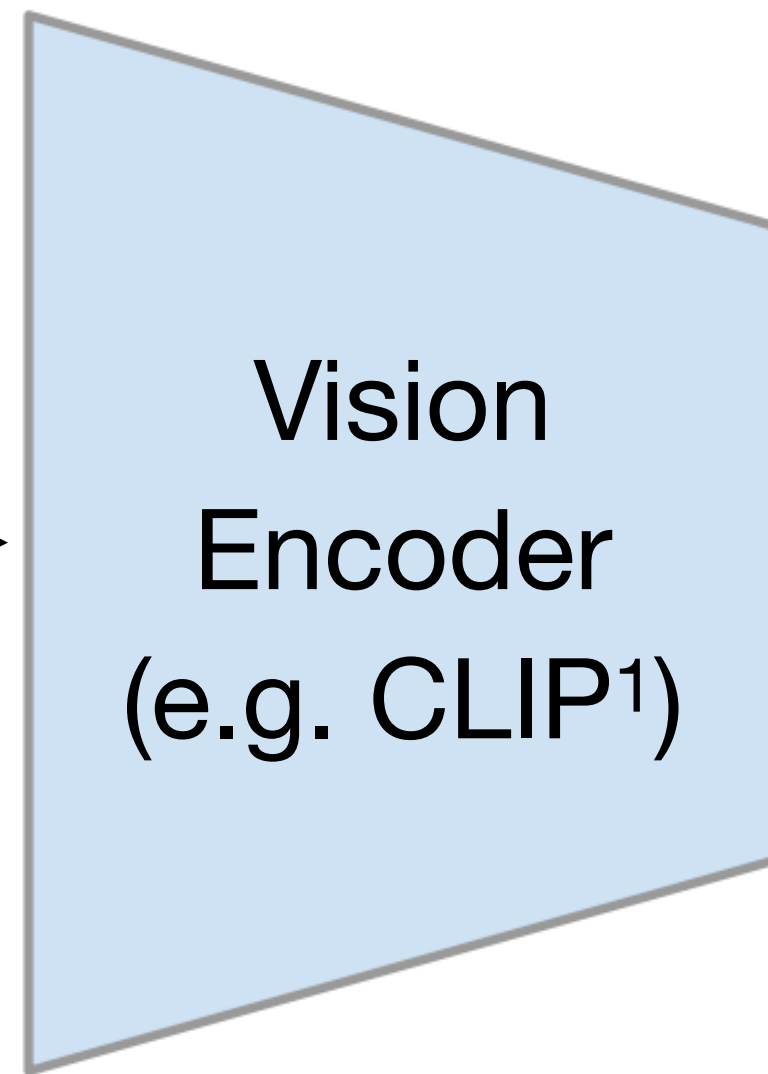
¹Radford et al. 2021

²Li et al. 2023

³Chung et al. 2023

Vision-Language Models (VLMs)

Input image



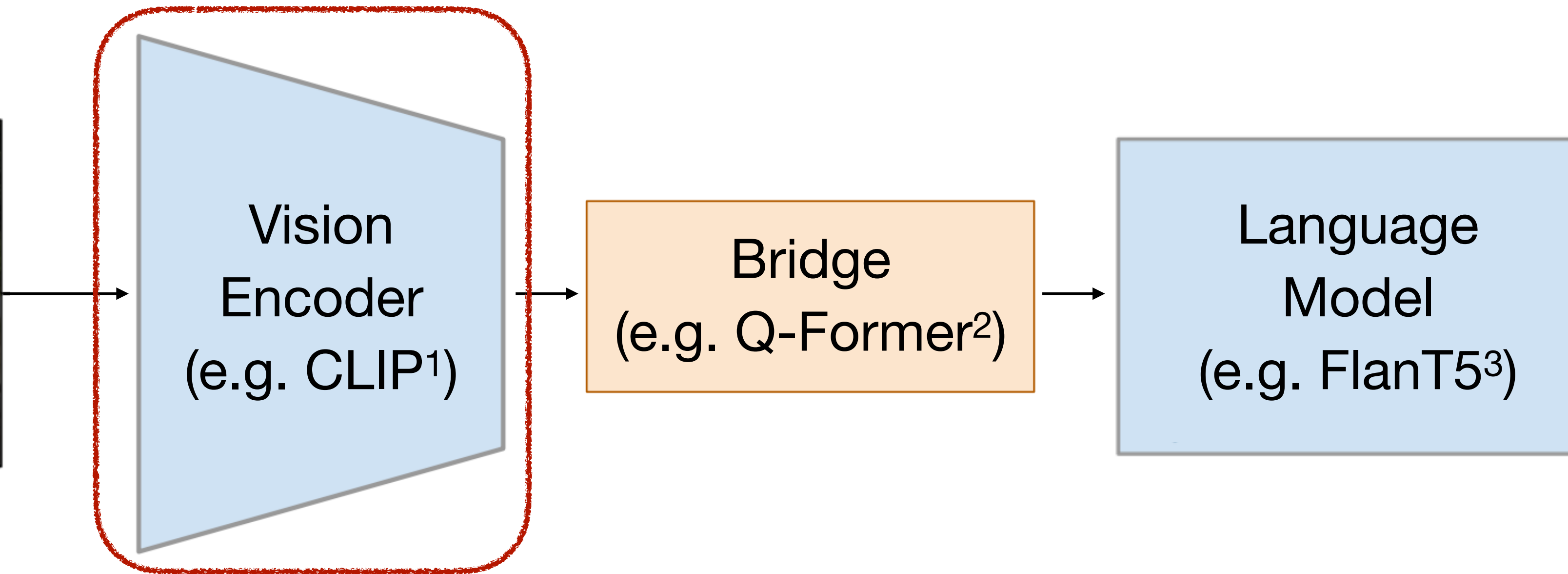
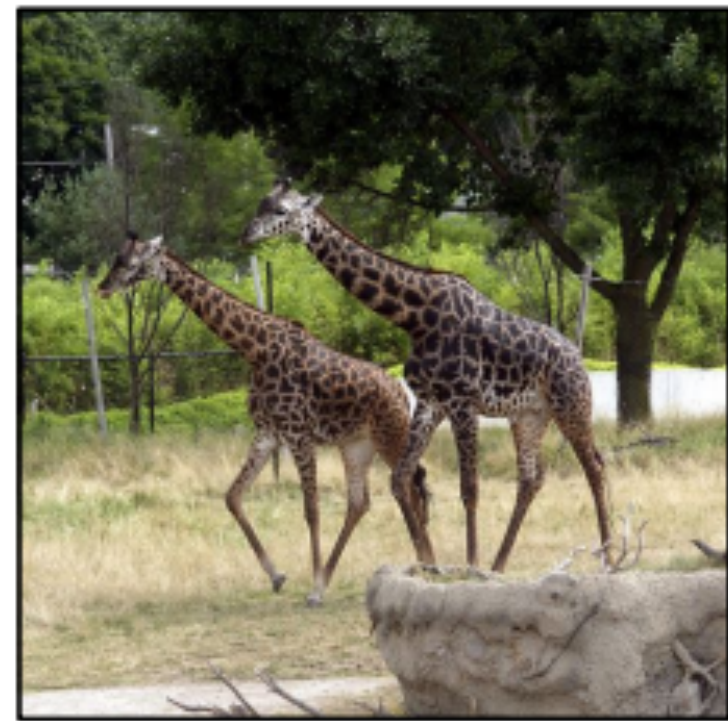
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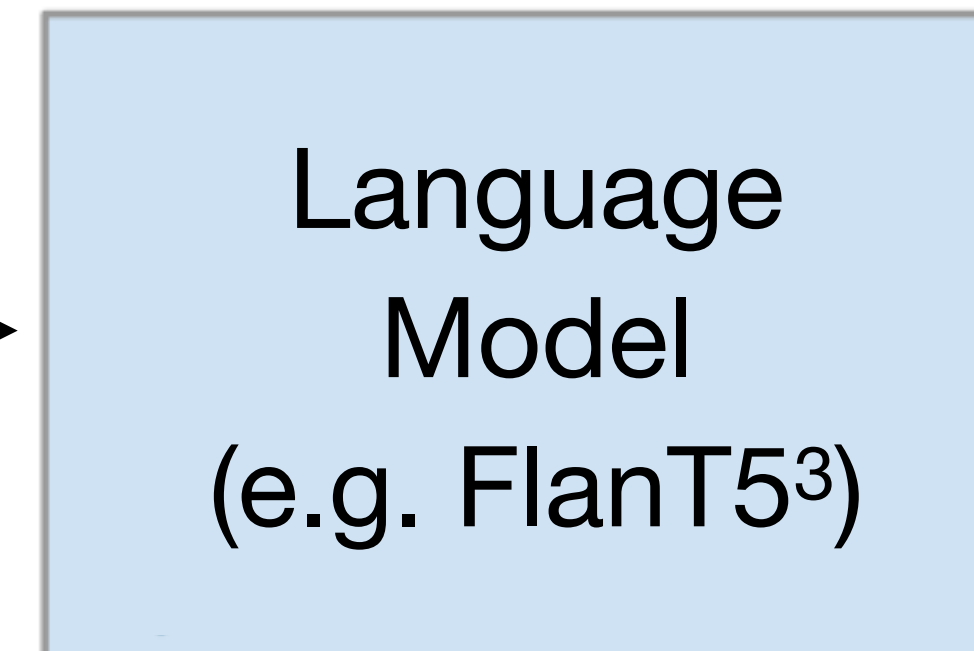
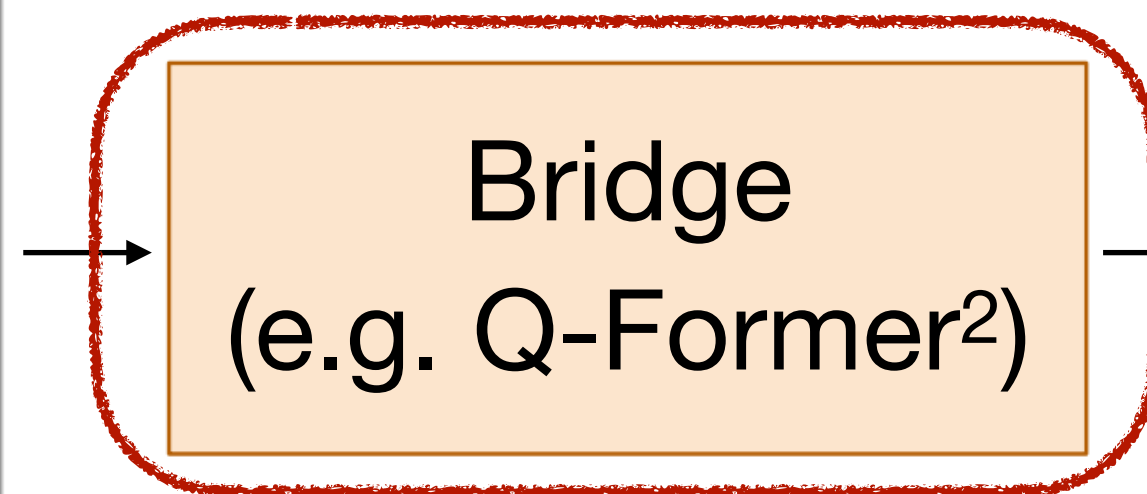
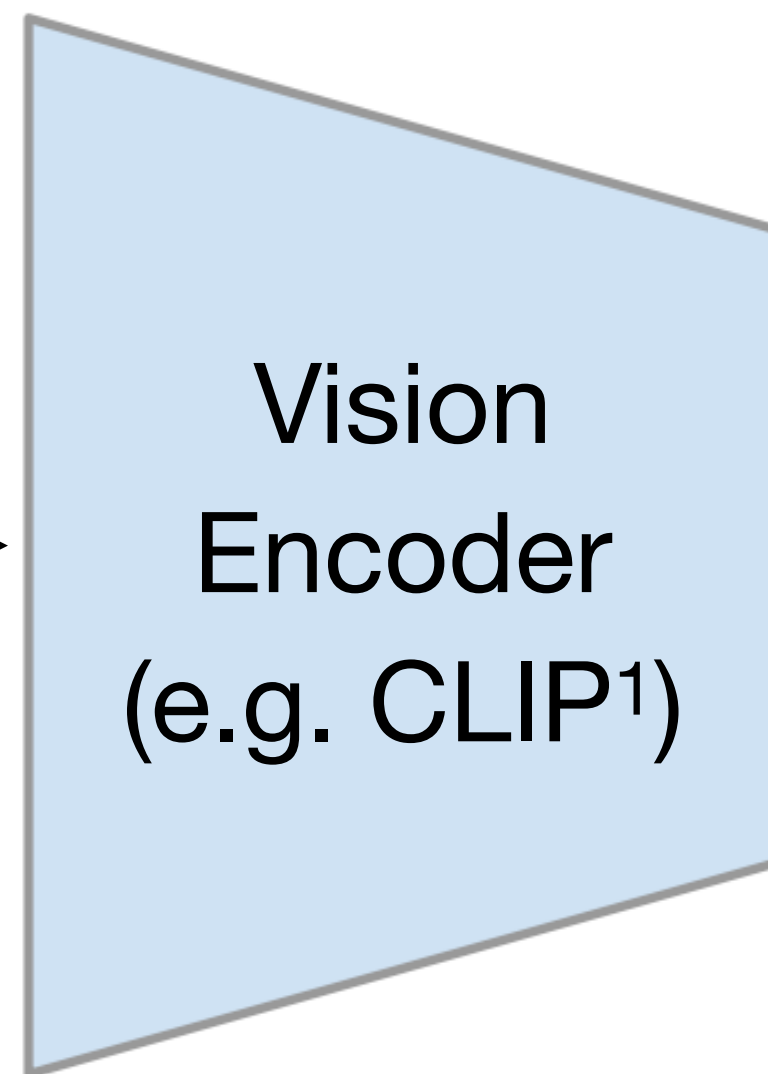
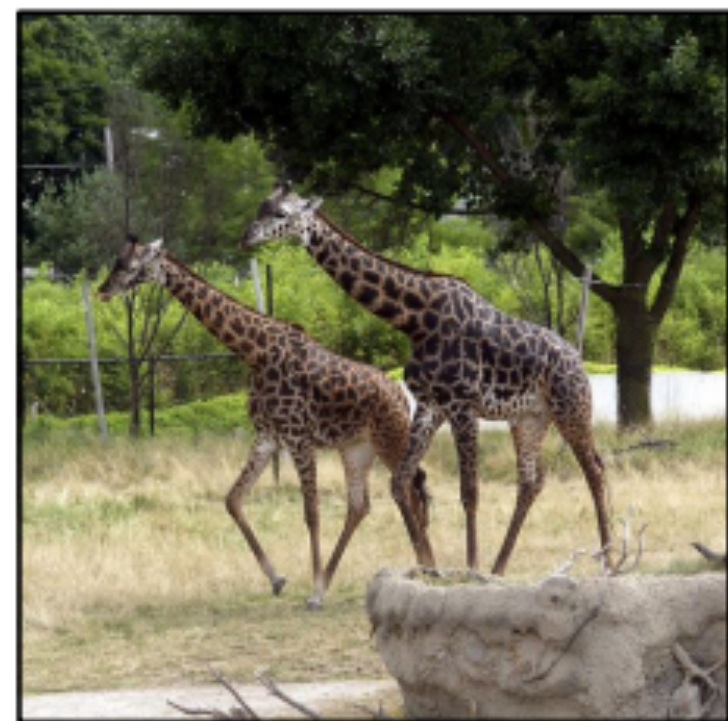
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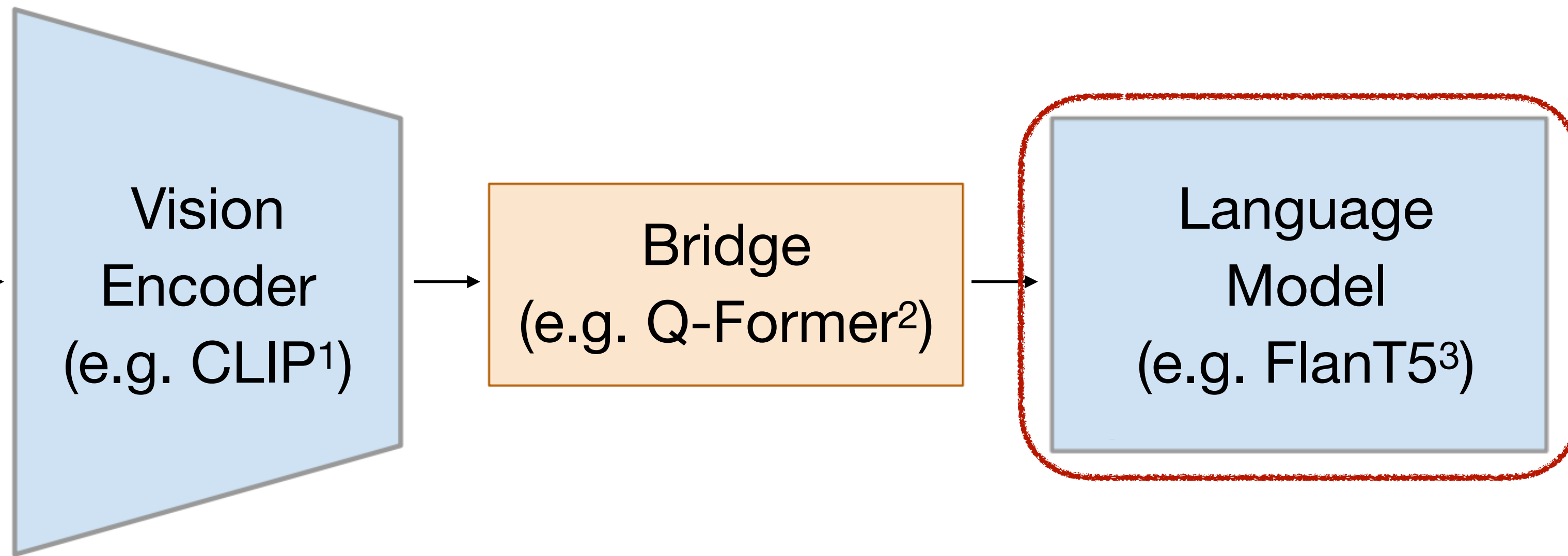
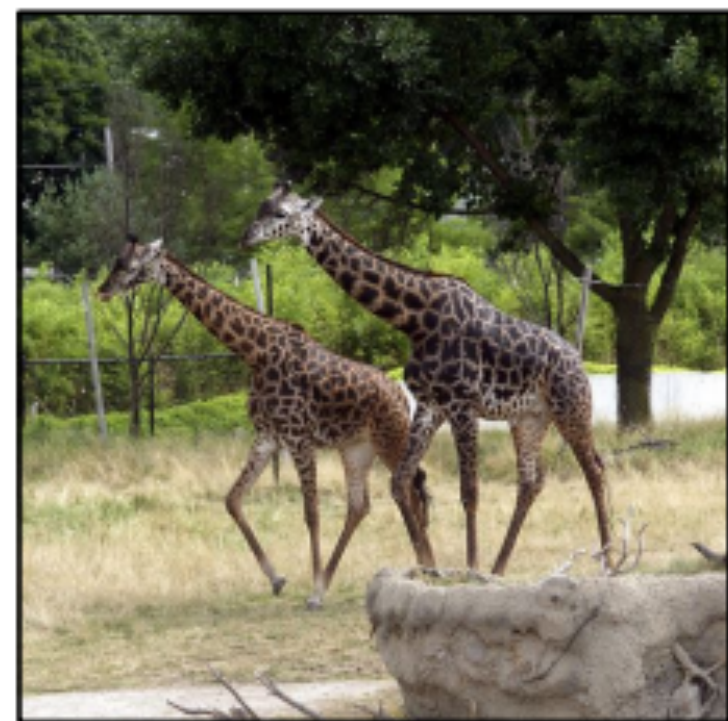
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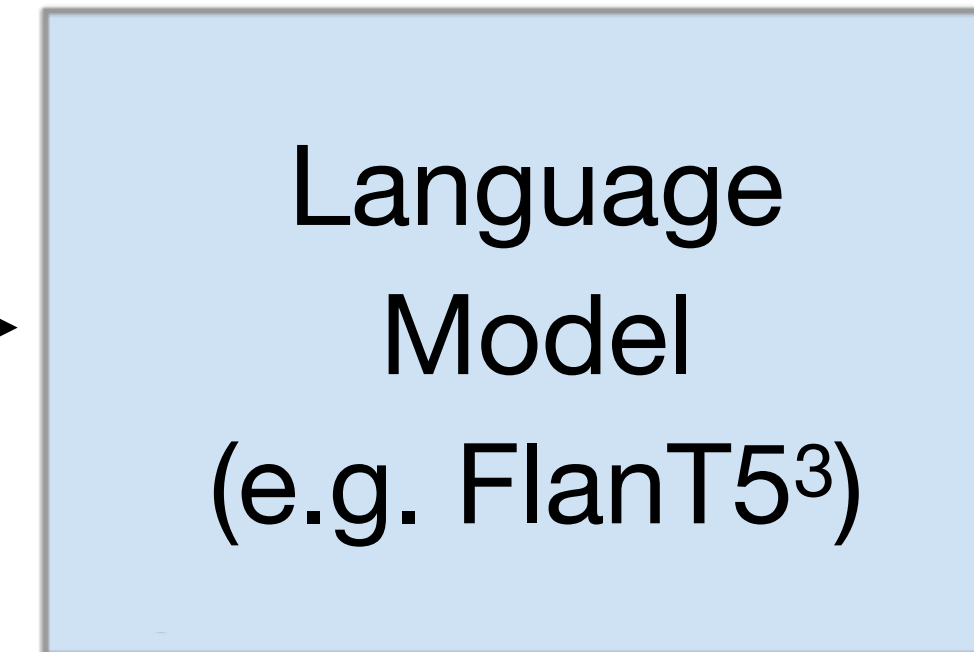
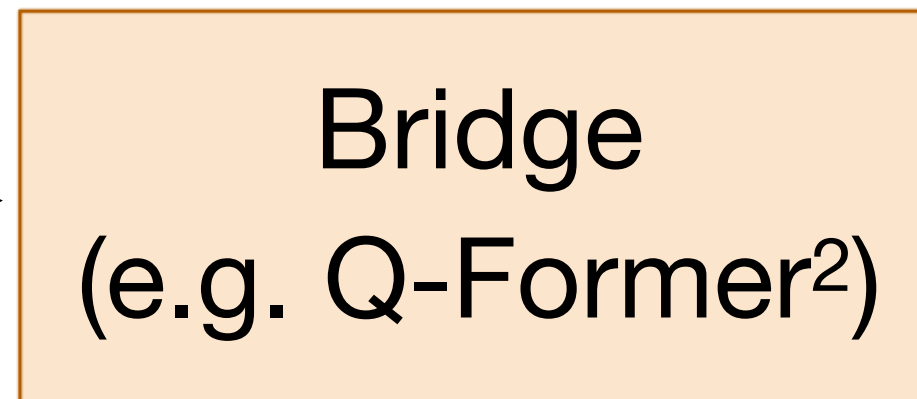
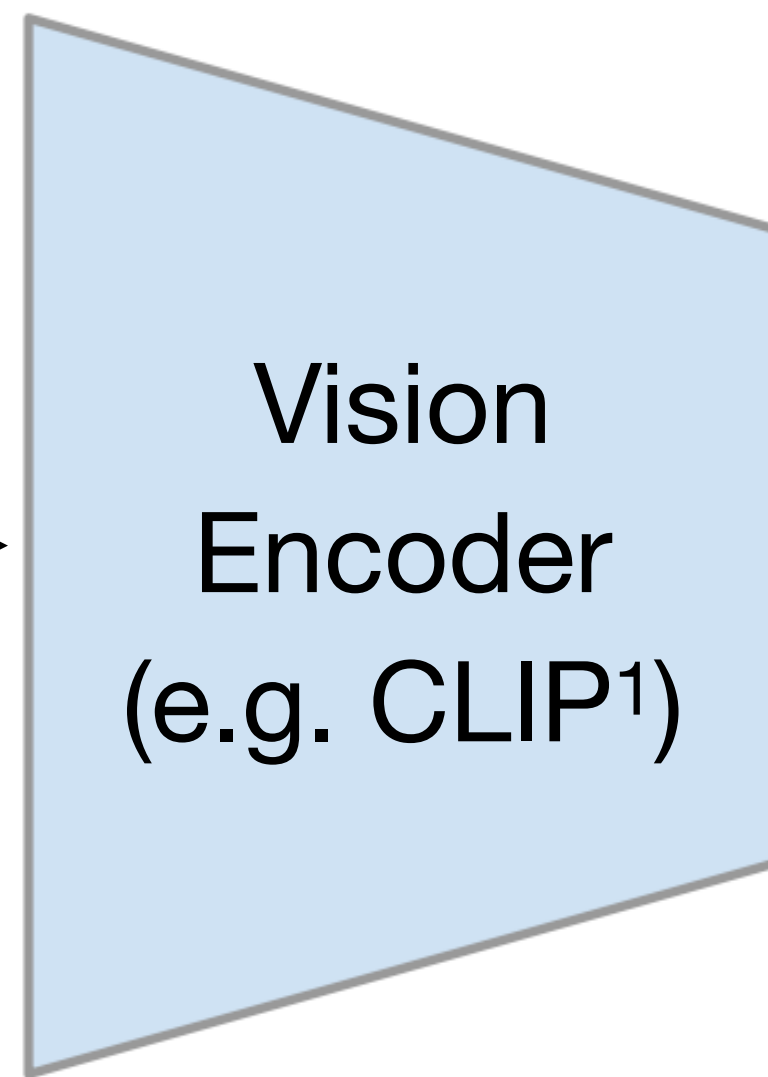
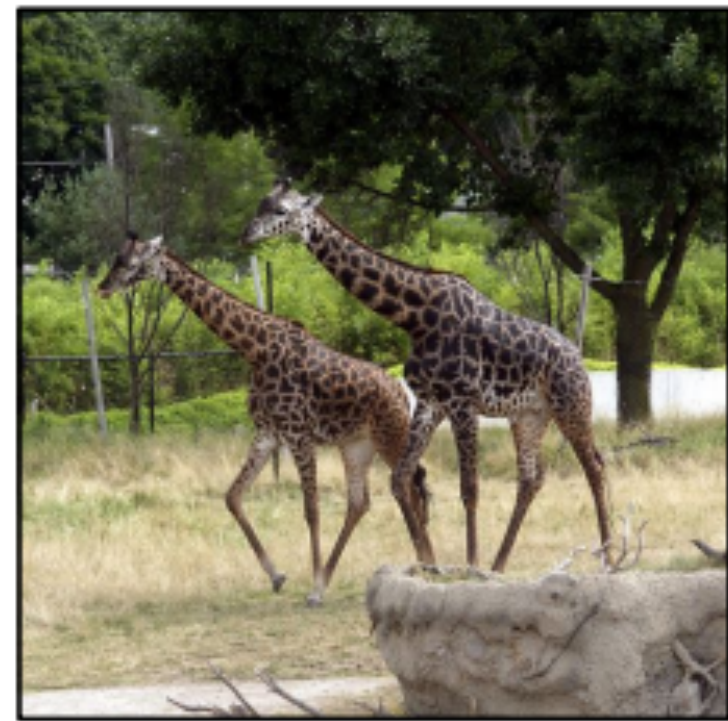
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Vision-Language Models (VLMs)

Input image



Output:
Captioning,
VQA, etc.

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²Li et al. 2023

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VLMs have important shortcomings

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- Limited language capabilities
 - Hallucinations^{1,2}
 - Logical faults^{3,4}

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 - “Blindness”⁵
 - Visual hallucinations⁶

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Our focus



¹Bang et al. 2023

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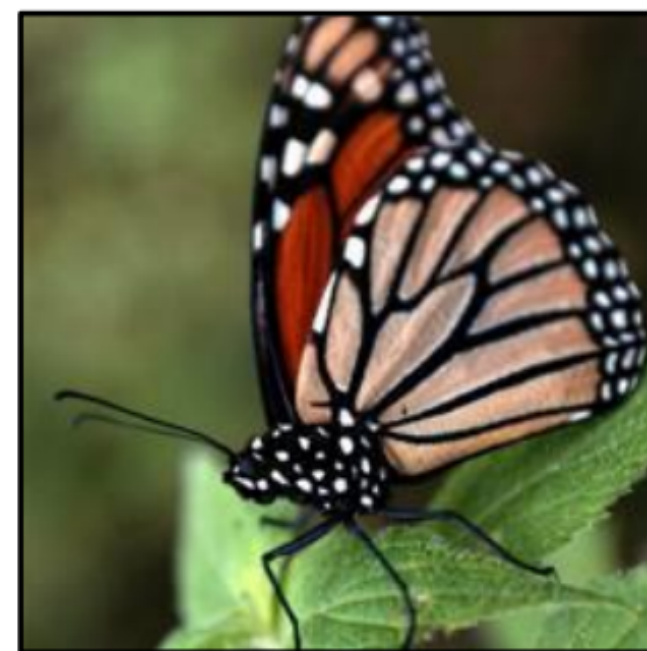
⁶Li et al. 2023

Example failures — confusing image pairs¹

Is there a hand using the mouse in this image?



Are the butterfly's feet visible?



Is the door of the truck open?

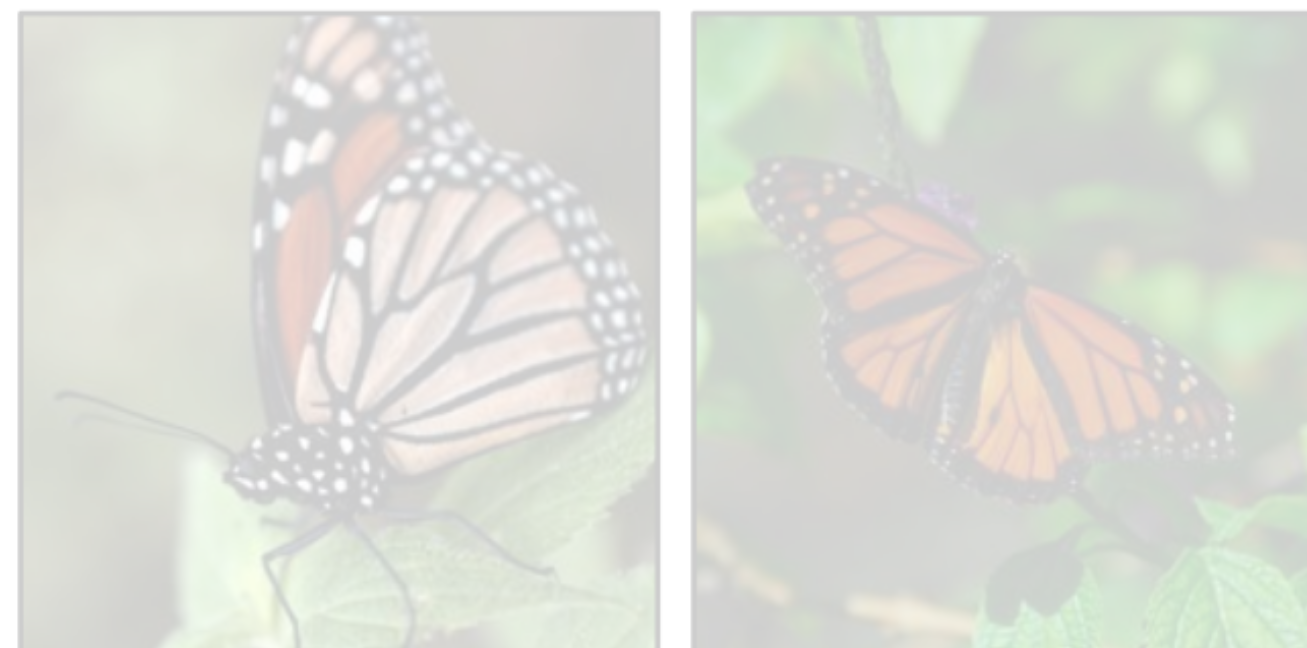


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InstructBLIP :

LLaVA-1.5 :

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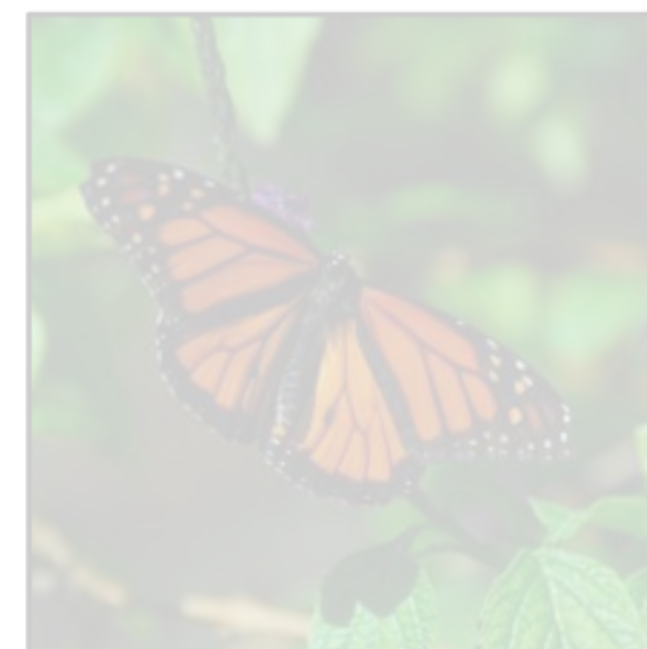
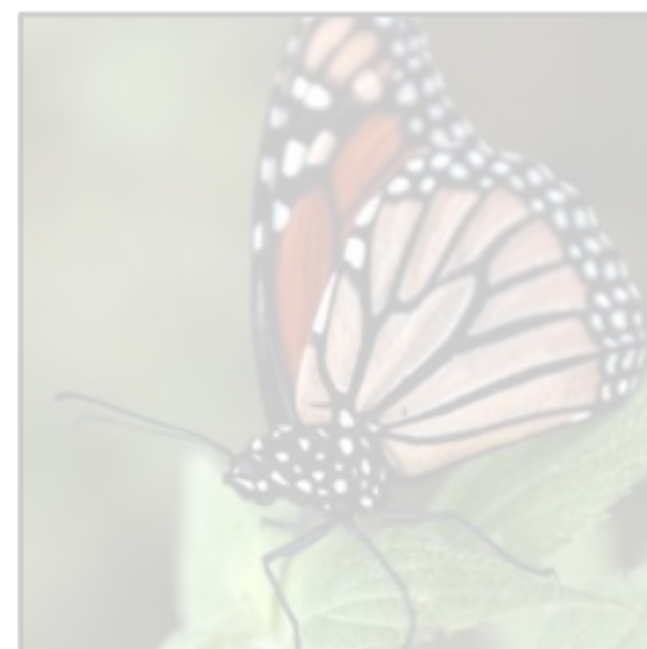


Yes

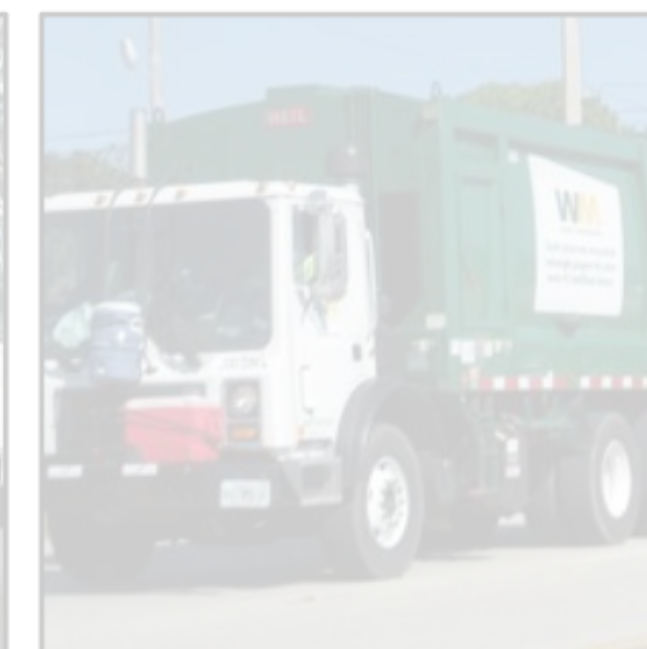


No

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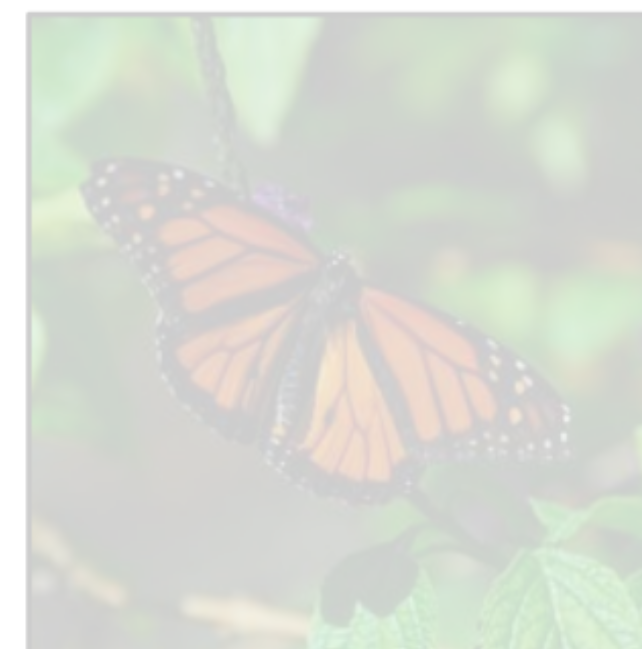
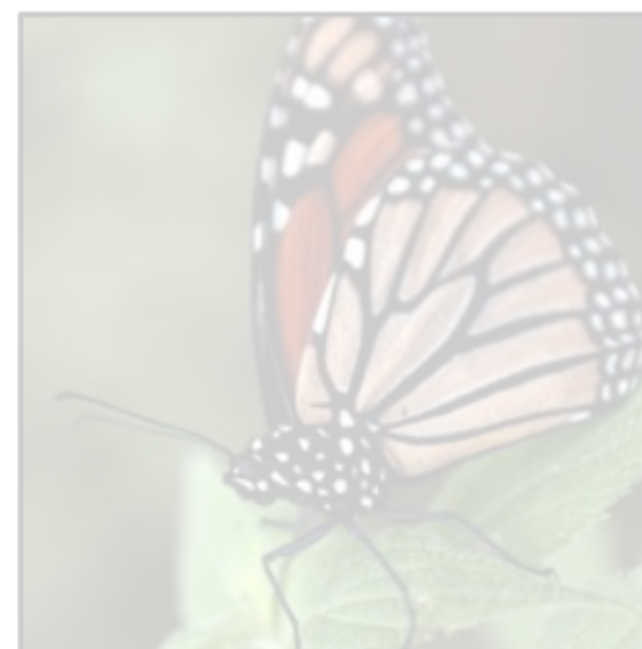
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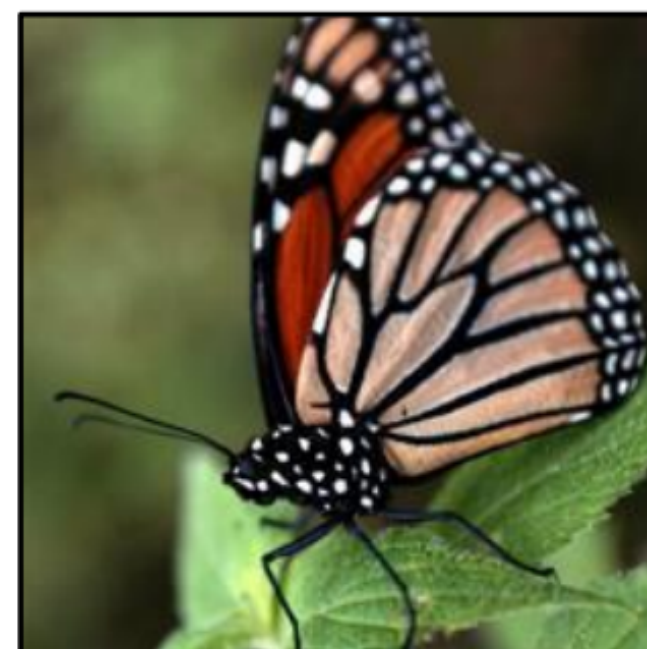


Yes



No

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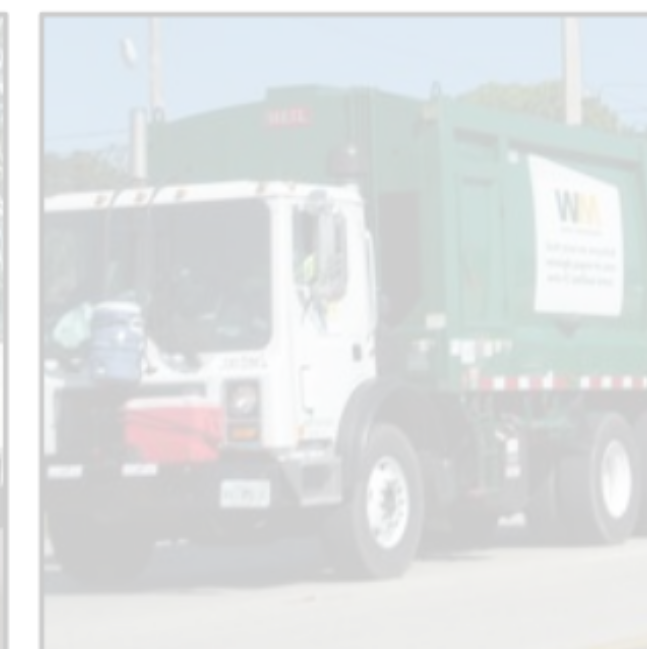


Yes



No

Is the door of the truck open?



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Yes

Yes

Yes

LLaVA-1.5 : No

No

Yes

No

Yes

Yes

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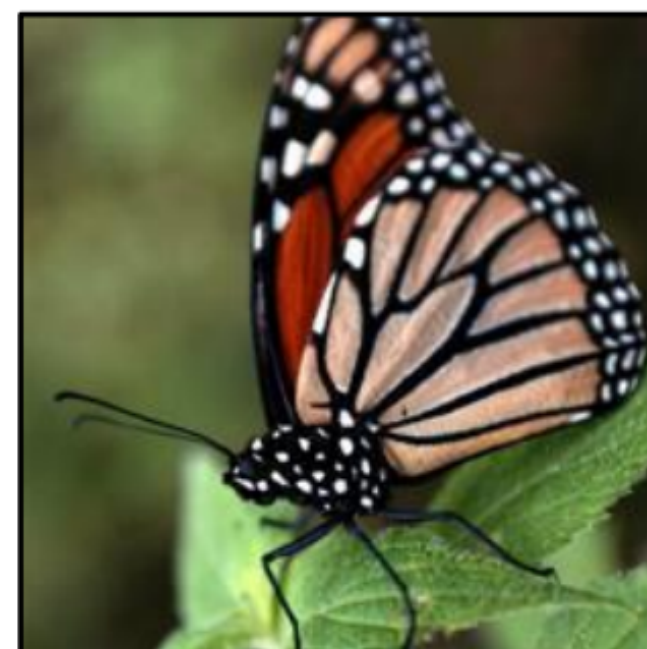


Yes



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Yes



No

InstructBLIP :
(EVA Encoder)

Yes

No



Yes

Yes



Yes

Yes



LLaVA-1.5 :
(CLIP Encoder)

No

No



Yes

No



Yes

Yes



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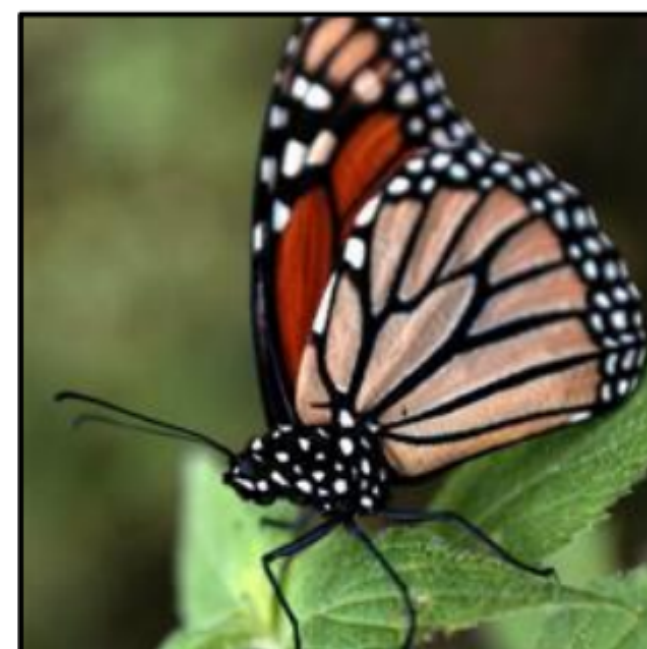


Yes



No

Are the butterfly's feet visible?



Yes



No

Is the door of the truck open?



Yes



No

InstructBLIP : Yes
(Ovr. Acc. 16.7%)

Yes

No

Yes

Yes

Yes

Yes

LLaVA-1.5 : No
(Ovr. Acc. 24.7%)

No

No

Yes

No

Yes

Yes

Example failures — confusing image pairs¹

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Yes



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(Ovr. Acc. 16.7%)

Yes

No

Yes

Yes

Yes

Yes

LLaVA-1.5 : No
(Ovr. Acc. 24.7%)

No


No

Yes

No

Yes

Yes

BRAVE  : Yes
(Ovr. Acc. 42.0%)

Yes

No

Yes

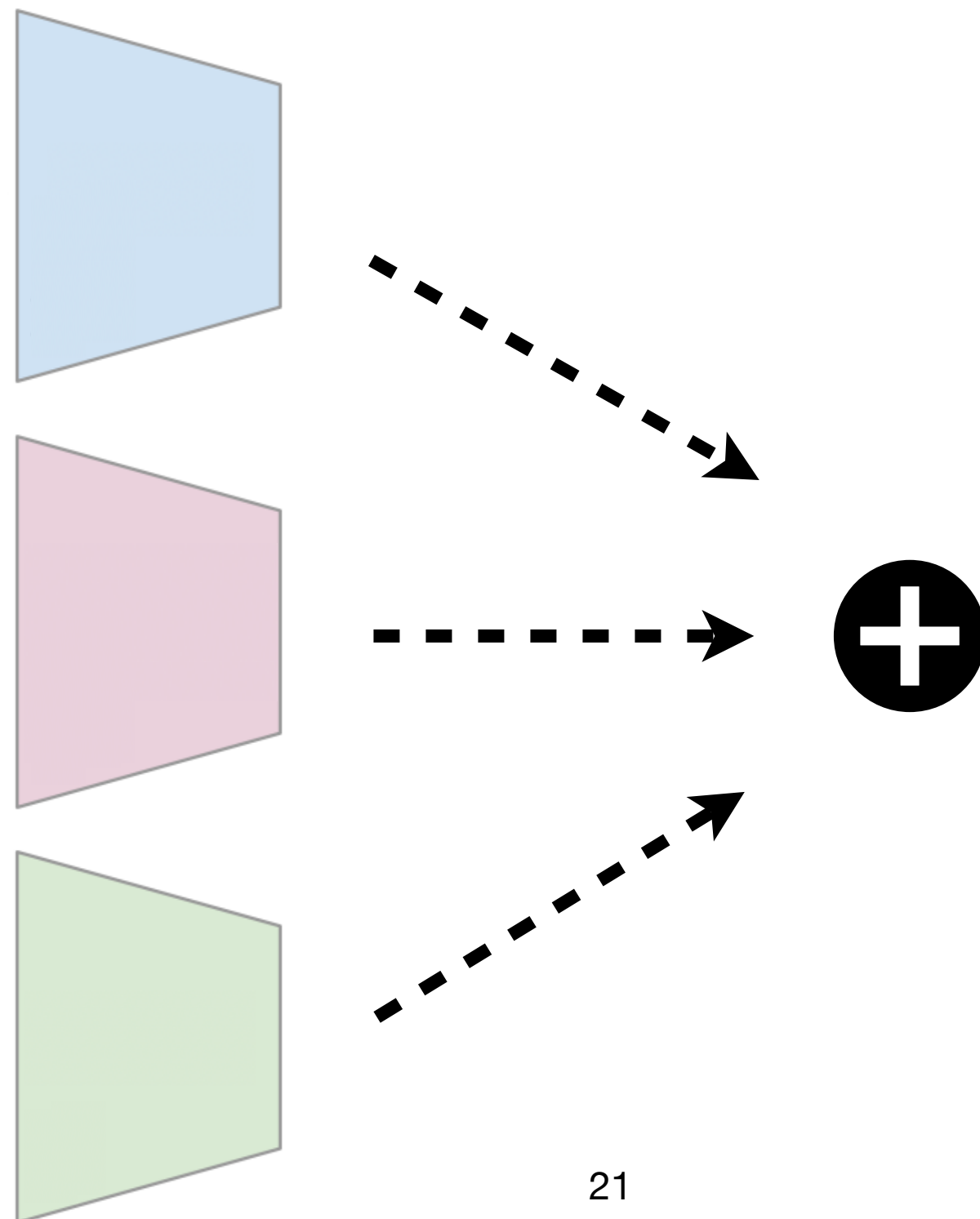
No

Yes

No

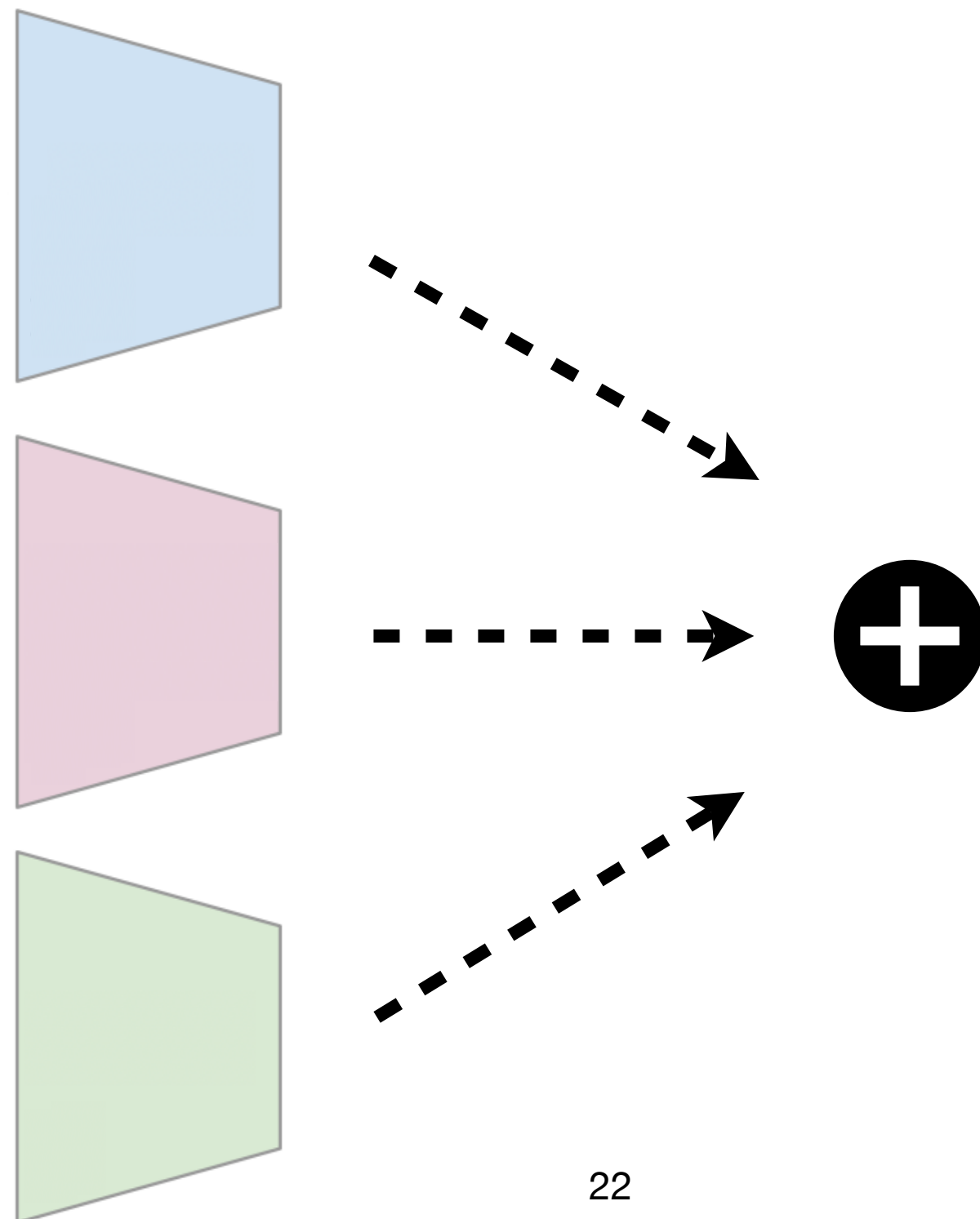
BRAVE: Broadening the visual encoding of VLMs

- Core idea from machine learning¹
 - Different representations -> Different generalization properties
 - Ensemble to create a more complete representation



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- Core idea from machine learning¹
 - Different representations -> Different generalization properties
 - Ensemble to create a more complete representation
 - Find the strongest set via **benchmarking**



Benchmarking vision encoders

- **8 different encoders**
 - Different objectives
 - Masked modeling, contrastive learning, etc.
 - Different training datasets
 - LAION-2B, JFT-3B, etc.
 - Different model sizes
 - 300M to 4B

Benchmarking vision encoders

- **8 different encoders**
 - Different objectives
 - Masked modeling, contrastive learning, etc.
 - Different training datasets
 - LAION-2B, JFT-3B, etc.
 - Different model sizes
 - 300M to 4B
- ***CLIP*¹, *EVA*², *DINOv2*³, *SIGLIP*⁴, *OpenCLIP*⁵, *SILC*⁶, *ViT-e*⁷, *ViT-G*⁸**
- **Evaluation tasks: Captioning, VQA**



⋮



¹Radford et al. 2021

²Fang et al. 2023

³Oquab et al. 2023

⁴Zhai et al. 2023

⁵Cherti et al. 2023

⁶Naeem et al. 2023

⁷Chen et al. 2022

⁸Zhai et al. 2022

Benchmarking vision encoders

Observations

- No encoder perform consistently well

Please see the paper for details



⋮



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- **No encoder perform consistently well**
 - Using a single encoder is inherently limited

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- **Encoders with different biases can perform similarly**

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Benchmarking vision encoders

Observations

- **No encoder perform consistently well**
 - Using a single encoder is inherently limited
- **Encoders with different biases can perform similarly**
 - Different cues to exploit

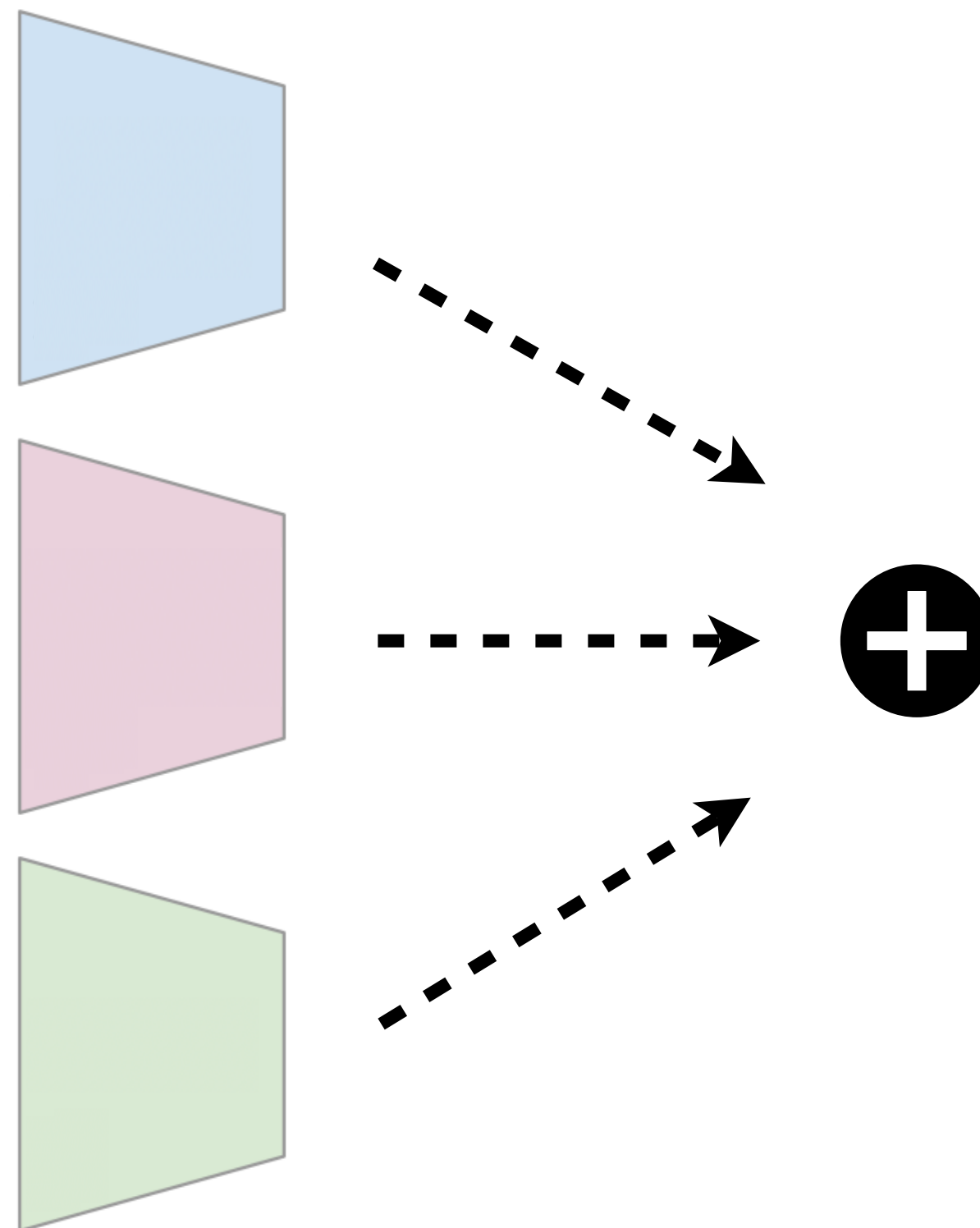
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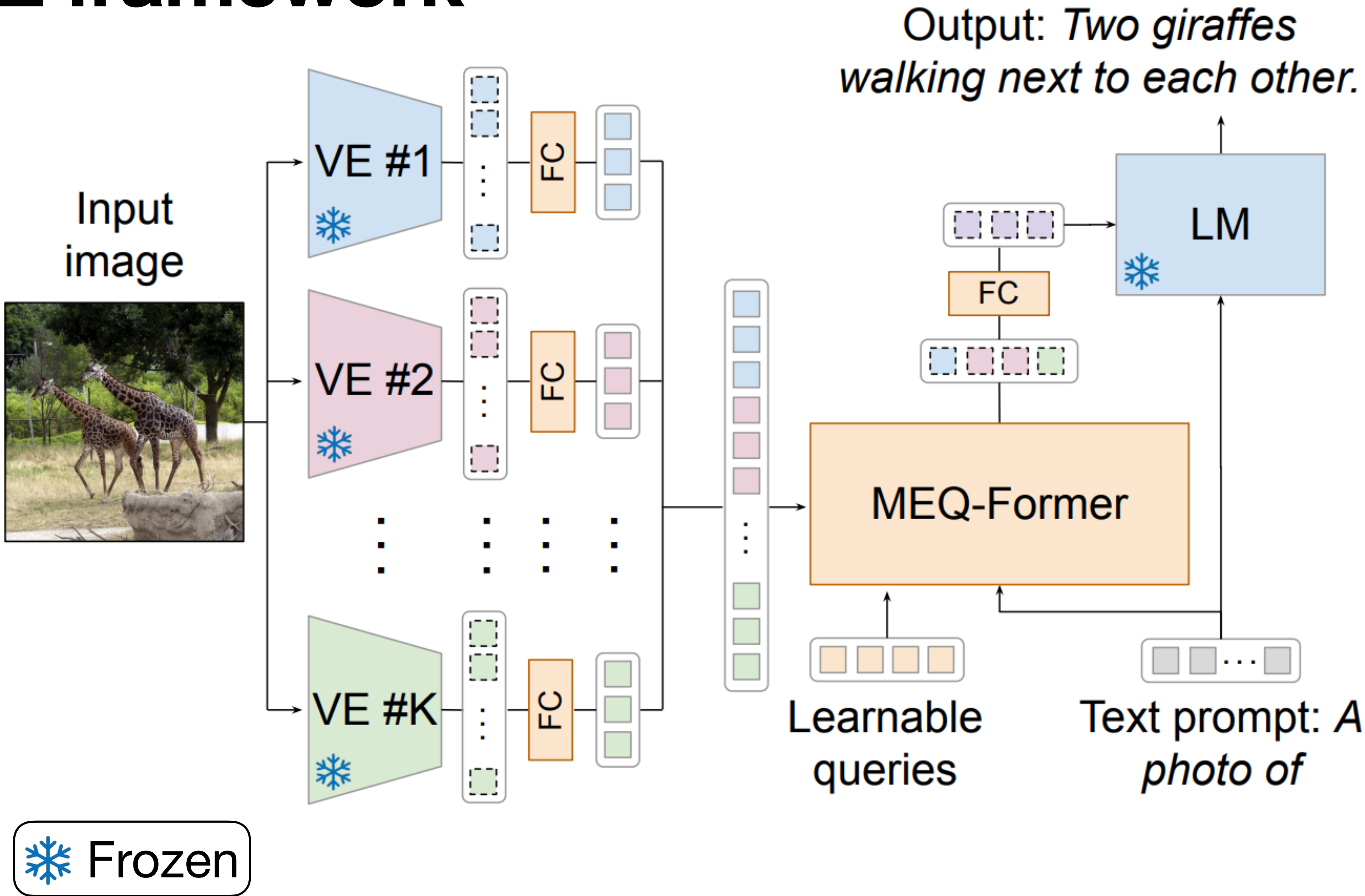
⋮



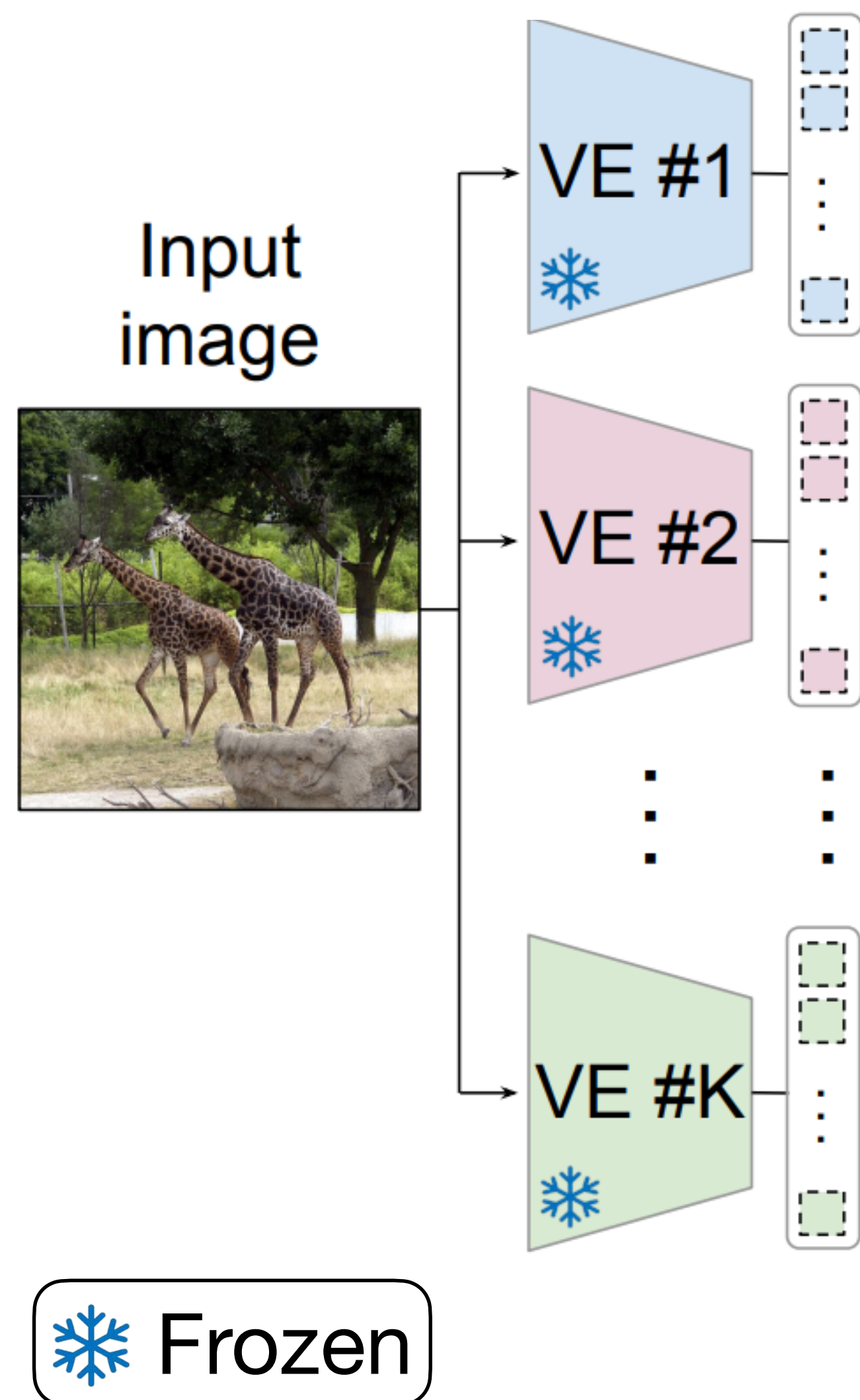
***Can we broaden the visual capabilities of VLMs
through combining vision encoders with different biases?***



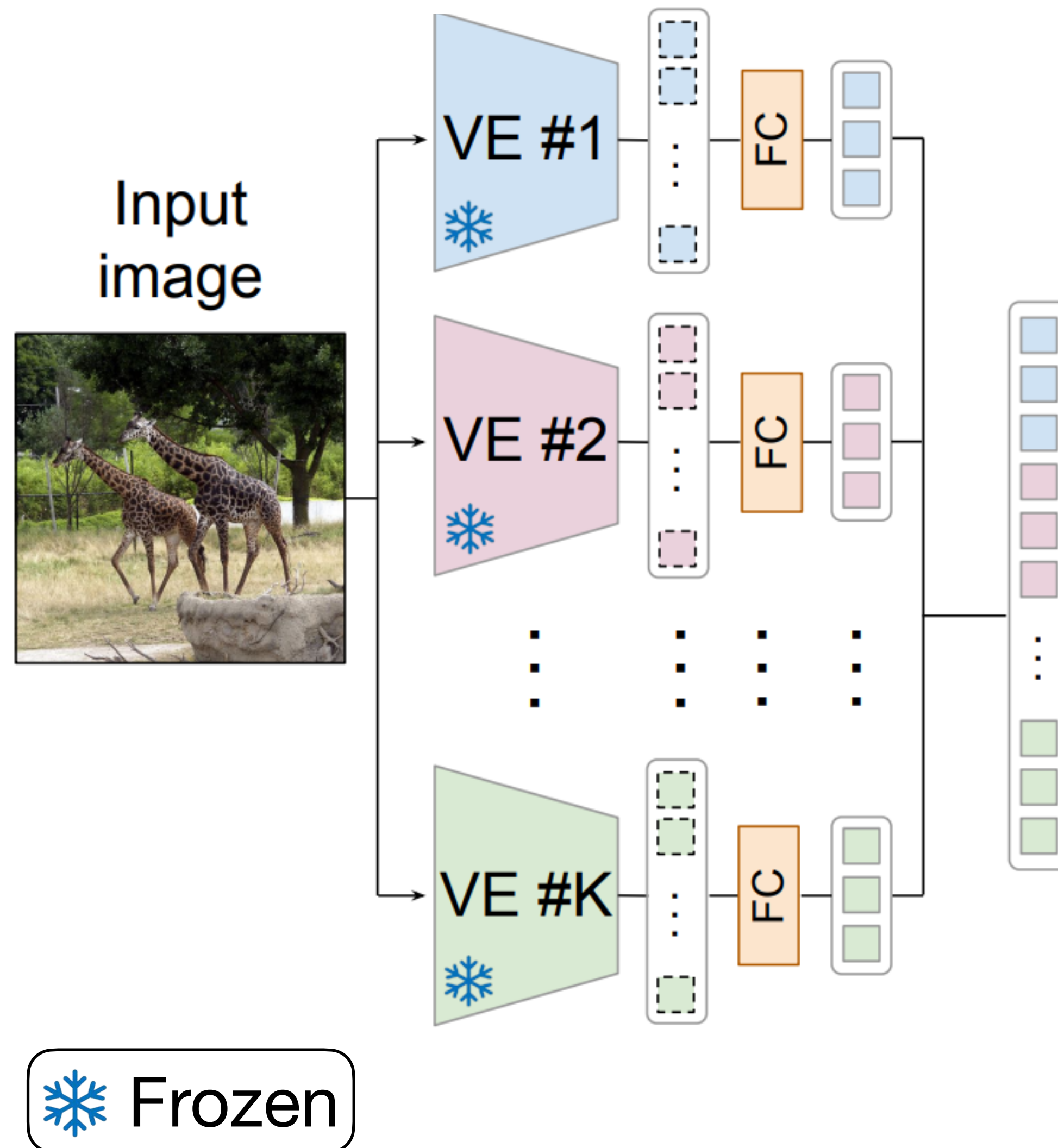
BRAVE framework



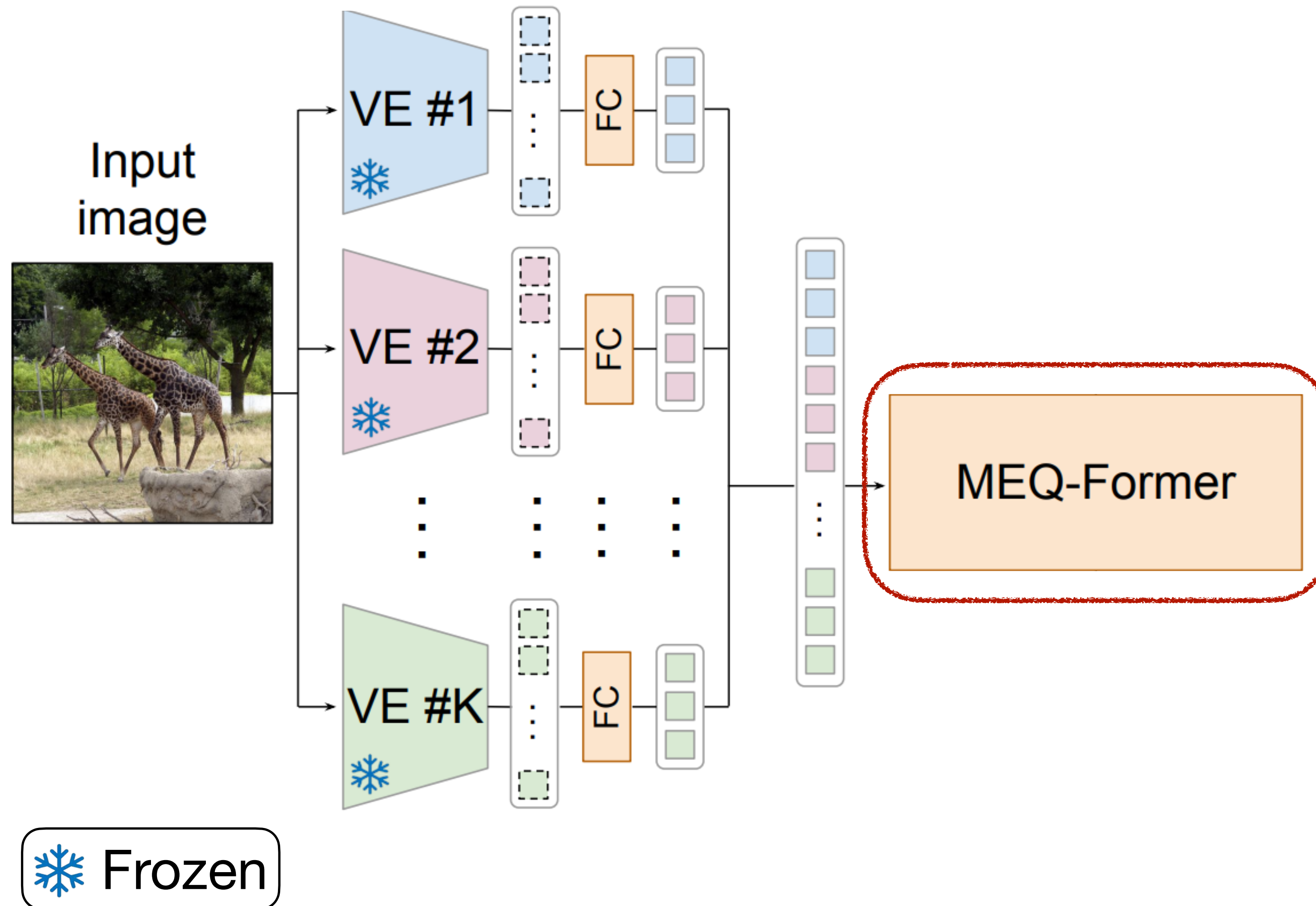
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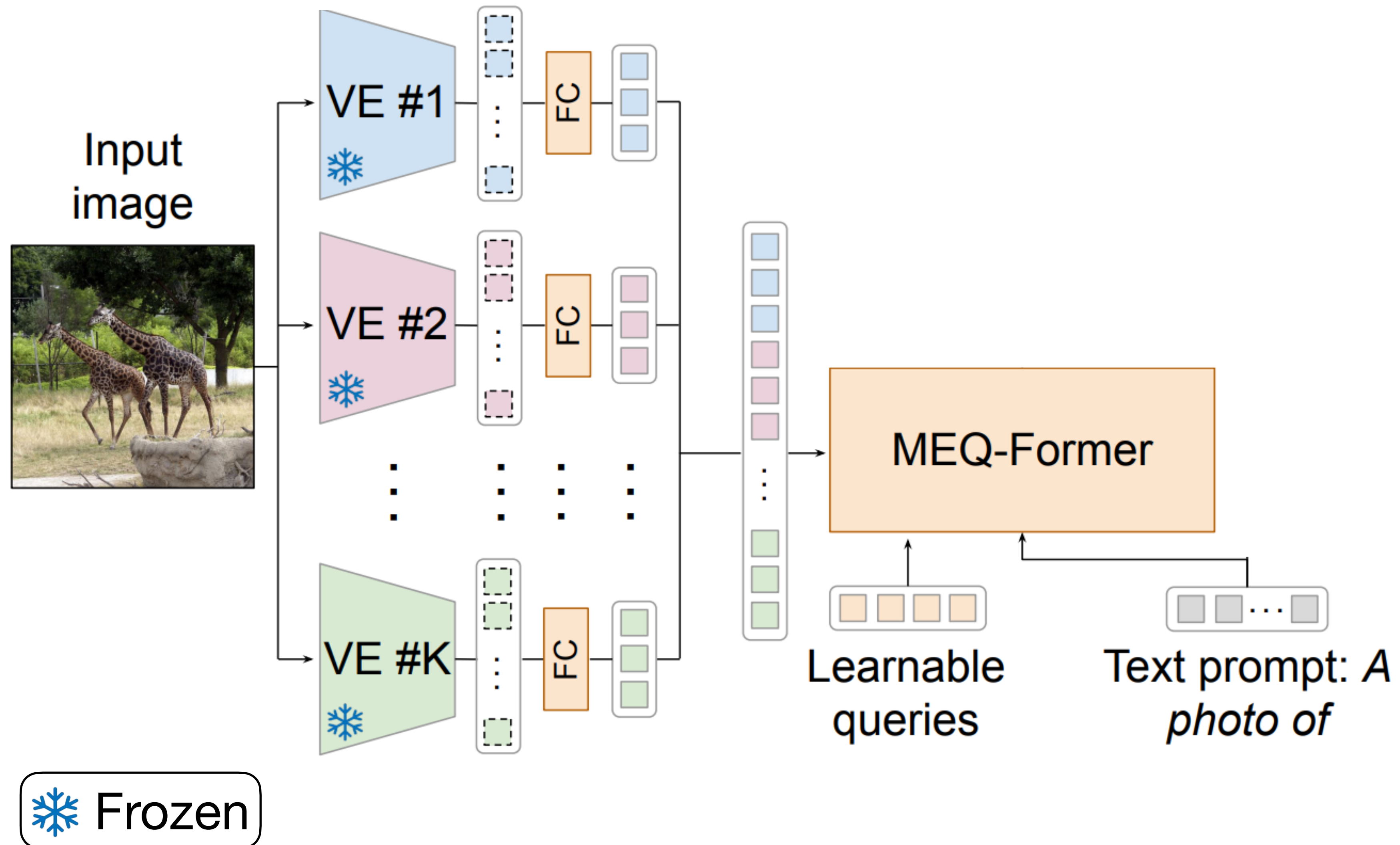
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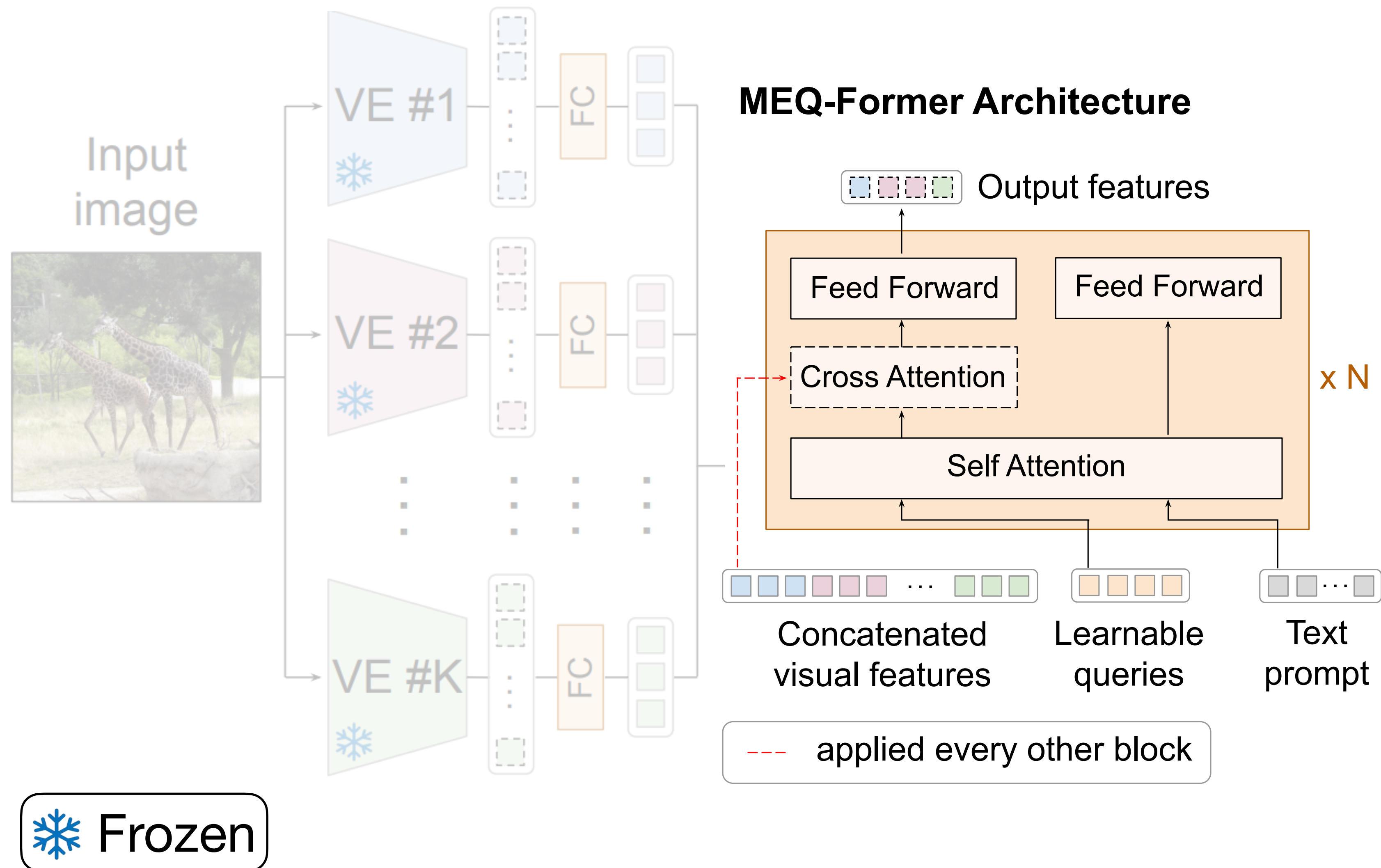
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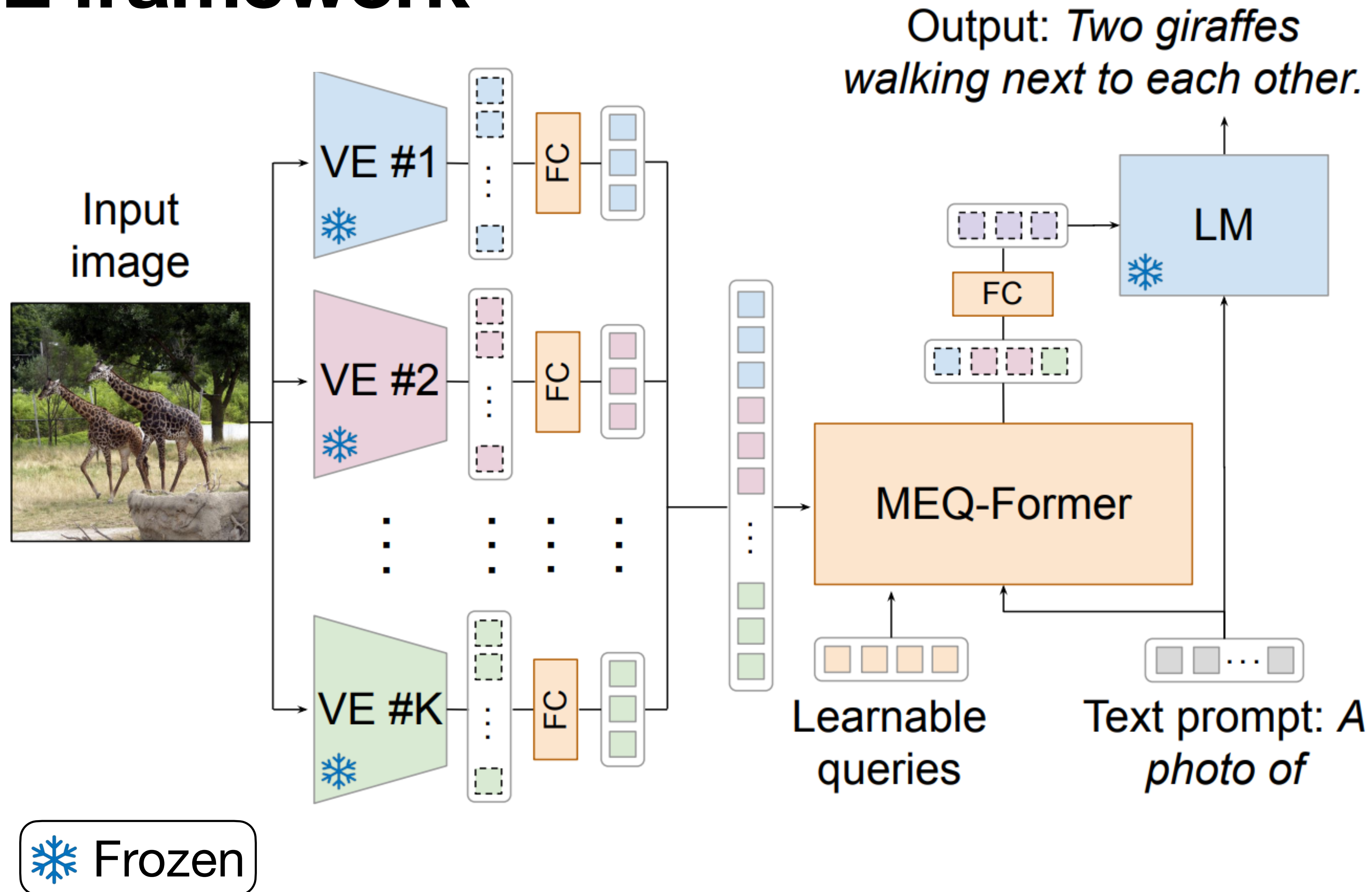
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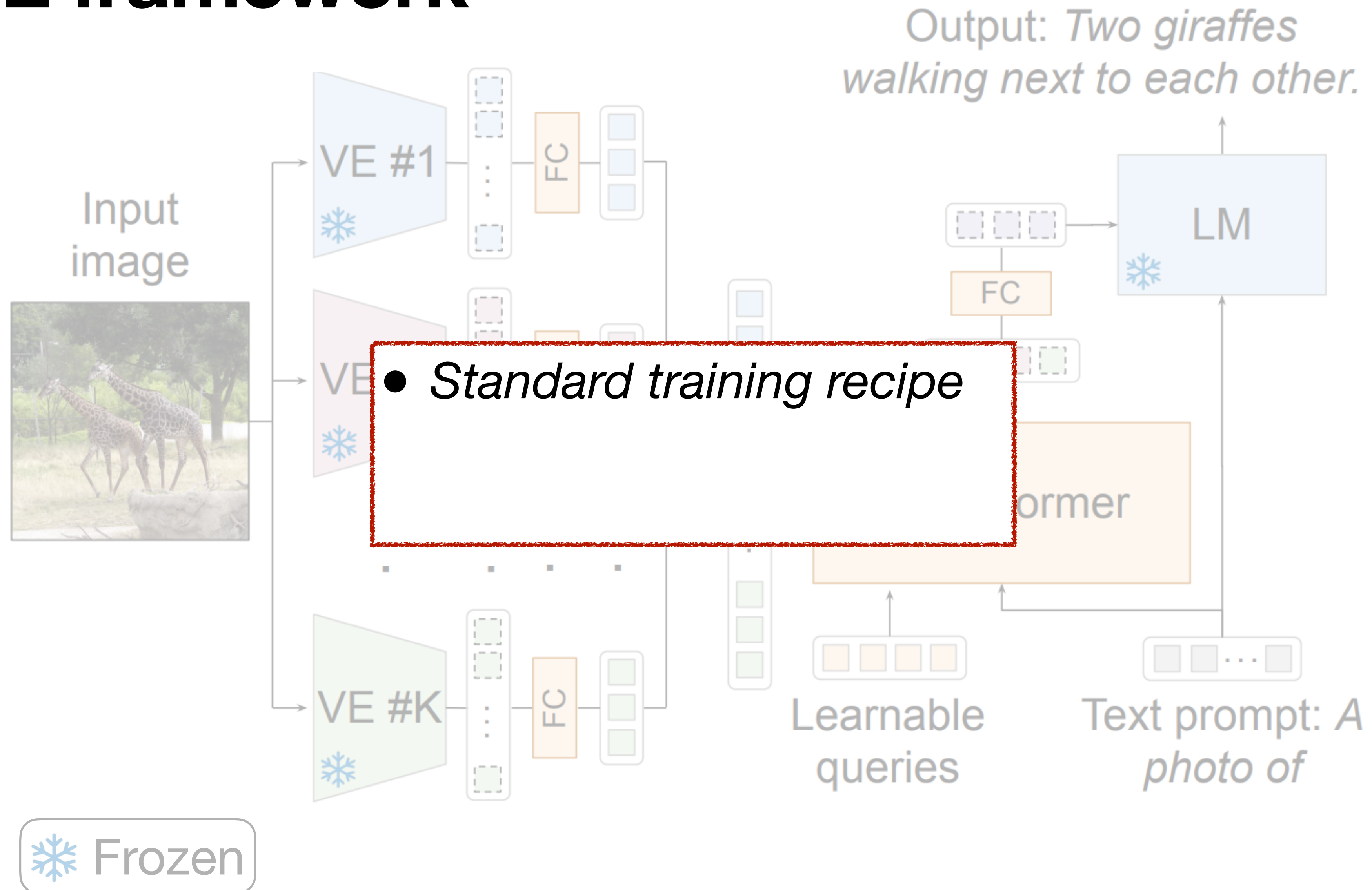
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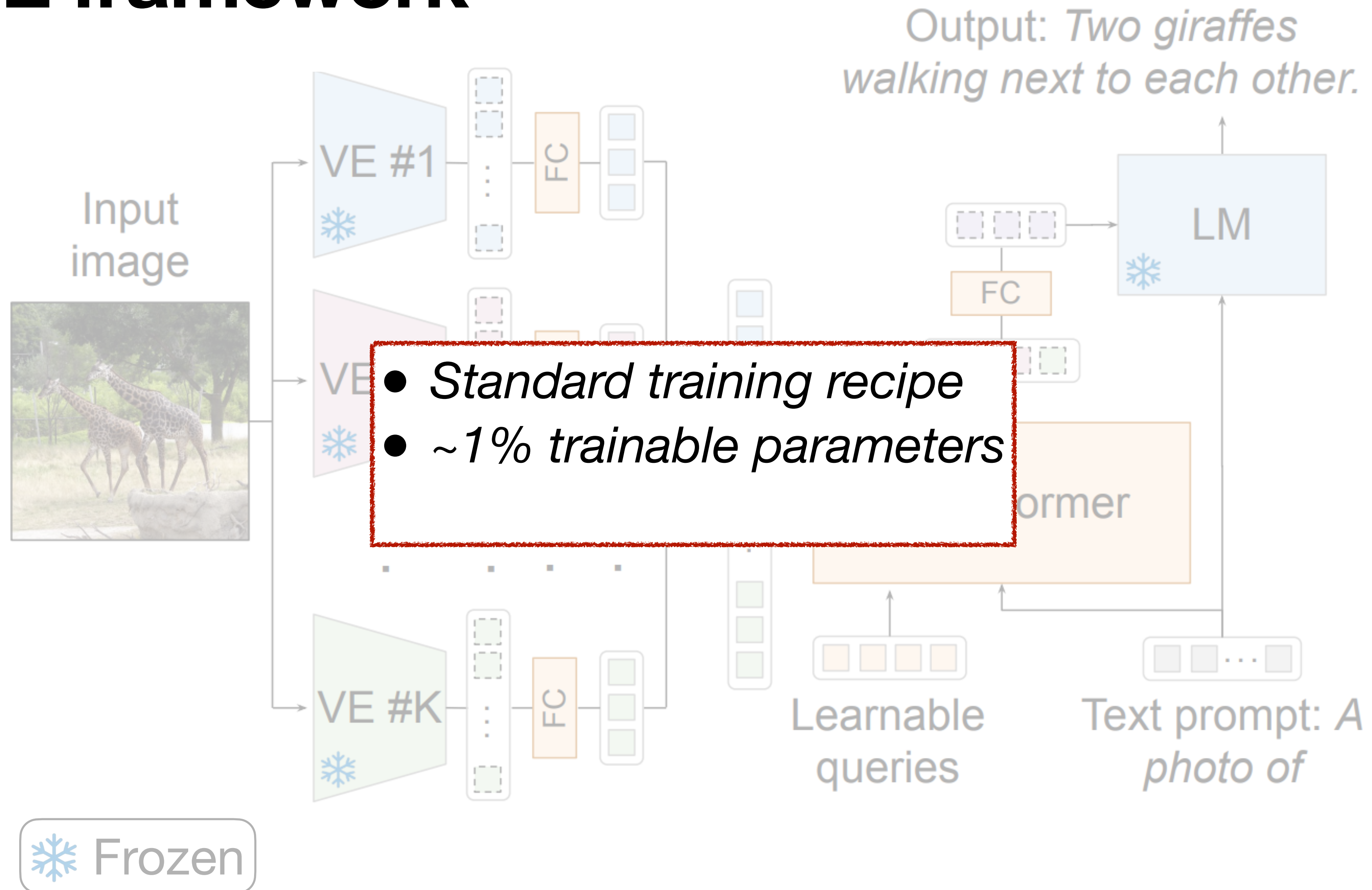
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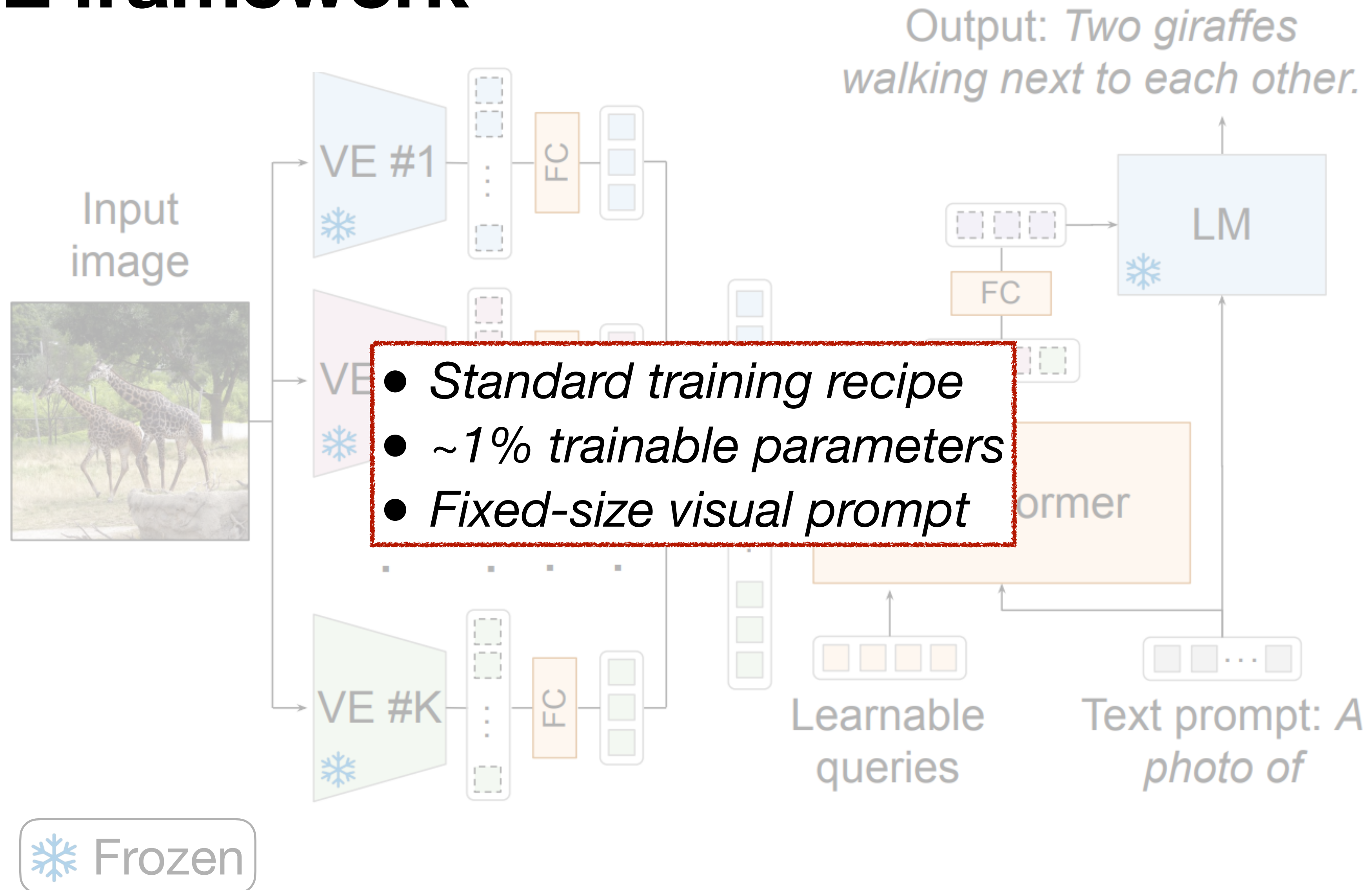
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Key results

- State-of-the-art performance for captioning & VQA tasks

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General Captioning



Caption: A large bus sitting next to a very tall building.

¹Chen et al. 2015

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Caption: A large bus sitting next to a very tall building.

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*Q: What color is the hydrant?
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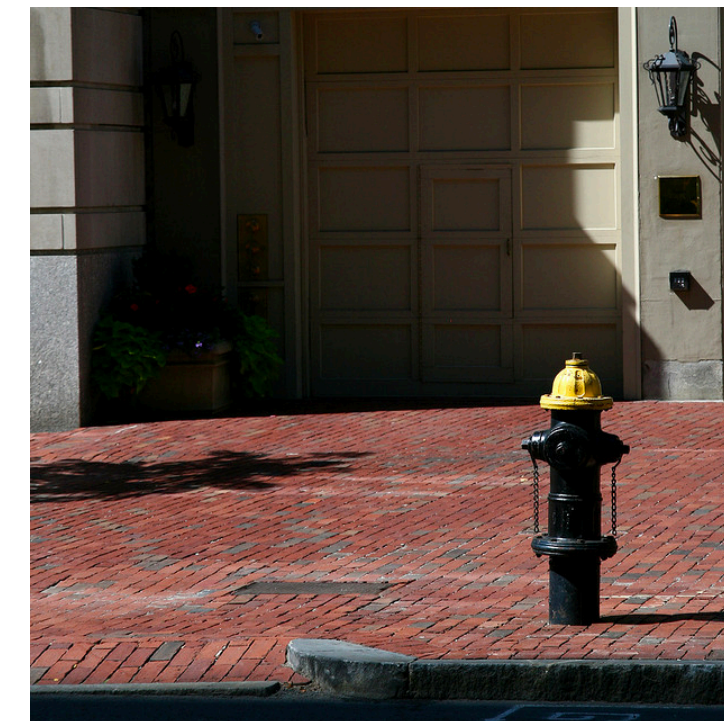
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Q: What company makes this sneakers? A: Converse

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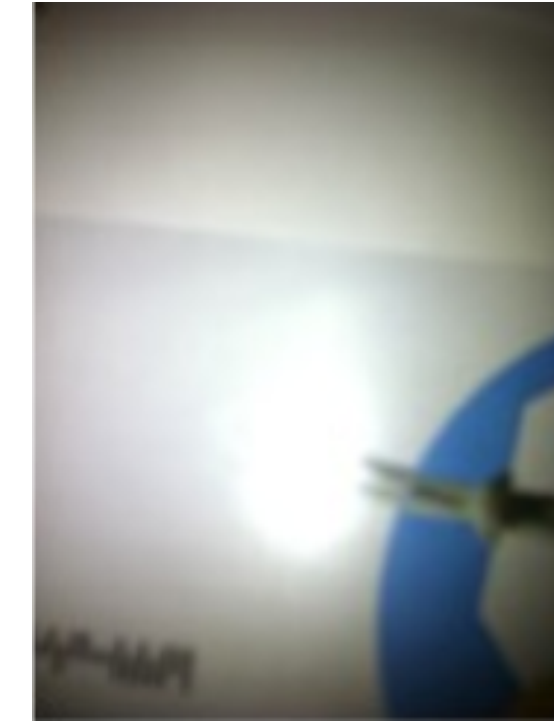
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Q: On which side of the image is the man? A: Right

VizWiz-QA⁶

Unanswerable Questions



*Q: Who is this mail for?
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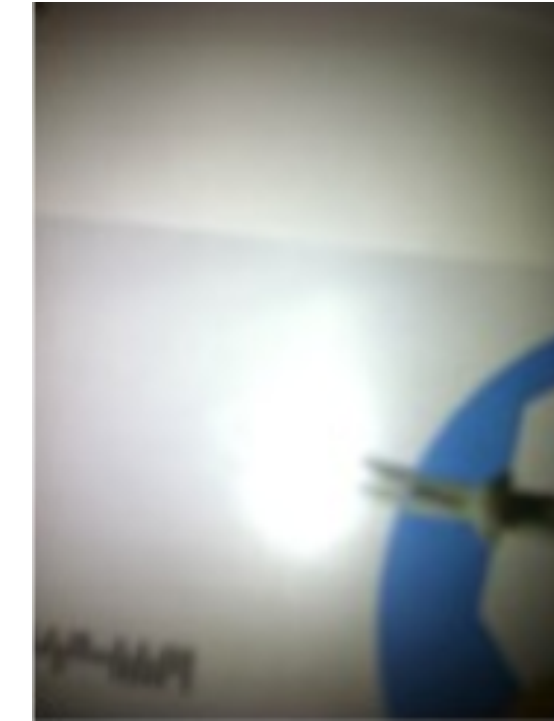
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- Improved robustness against hallucinations & confusing images

POPE¹

Visual Hallucination



Q: Is there a bottle in the image? A: No.



Q: Is there a surfboard in the image? A: No.

MMVP²

Confusing Pairs



Q: Are there cookies stacked on top of other cookies? A (Left): Yes - A (Right): No.

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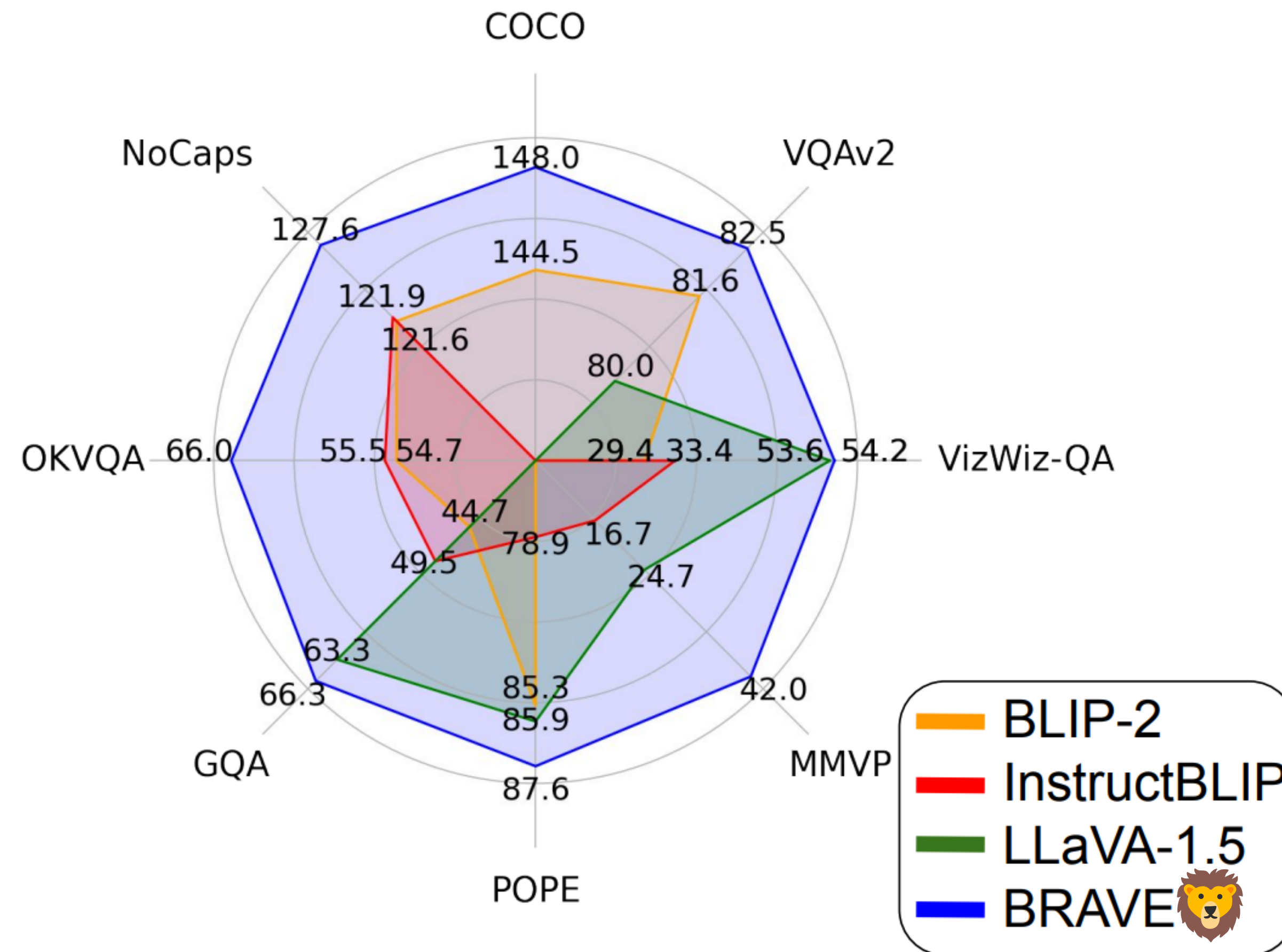


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Quantitative results – Captioning

Method	# params		COCO (fine-tuned)	NoCaps (zero-shot, val)		NoCaps (zero-shot, test)	
	Trainable	Total	Karpathy test	out-domain	overall	out-domain	overall
Flamingo [3]	10.6B	80B	138.1	-	-	-	-
SimVLM [85]	632M	632M	143.3	113.7	112.2	-	110.3
Qwen-VL [5]	9.6B	9.6B	-	-	121.4	-	-
BLIP-2 [53]	1.1B	4.1B	144.5	124.8	121.6	-	-
InstructBLIP [23]	188M	14.2B	-	-	121.9	-	-
CoCa [90]	2.1B	2.1B	143.6	-	122.4	-	120.6
GiT2 [81]	5.1B	5.1B	145.0	<u>130.6</u>	126.9	122.3	<u>124.8</u>
PaLI-17B [17]	16.9B	16.9B	149.1	-	127.0	126.7	124.4
BRAVE 	116M	10.3B	<u>148.0</u>	133.3	127.6	127.1	125.6


Quantitative results – Captioning

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SimVLM [85]	632M	632M	143.3	113.7	112.2	-	110.3
Qwen-VL [5]	9.6B	9.6B	-	-	121.4	-	-
BLIP-2 [53]	1.1B	4.1B	144.5	124.8	121.6	-	-
InstructBLIP [23]	188M	14.2B	-	-	121.9	-	-
CoCa [90]	2.1B	2.1B	143.6	-	122.4	-	120.6
GiT2 [81]	5.1B	5.1B	145.0	<u>130.6</u>	126.9	122.3	<u>124.8</u>
PaLI-17B [17]	16.9B	16.9B	149.1	-	<u>127.0</u>	<u>126.7</u>	124.4
BRAVE 	116M	10.3B	<u>148.0</u>	133.3	127.6	127.1	125.6

Quantitative results – VQA

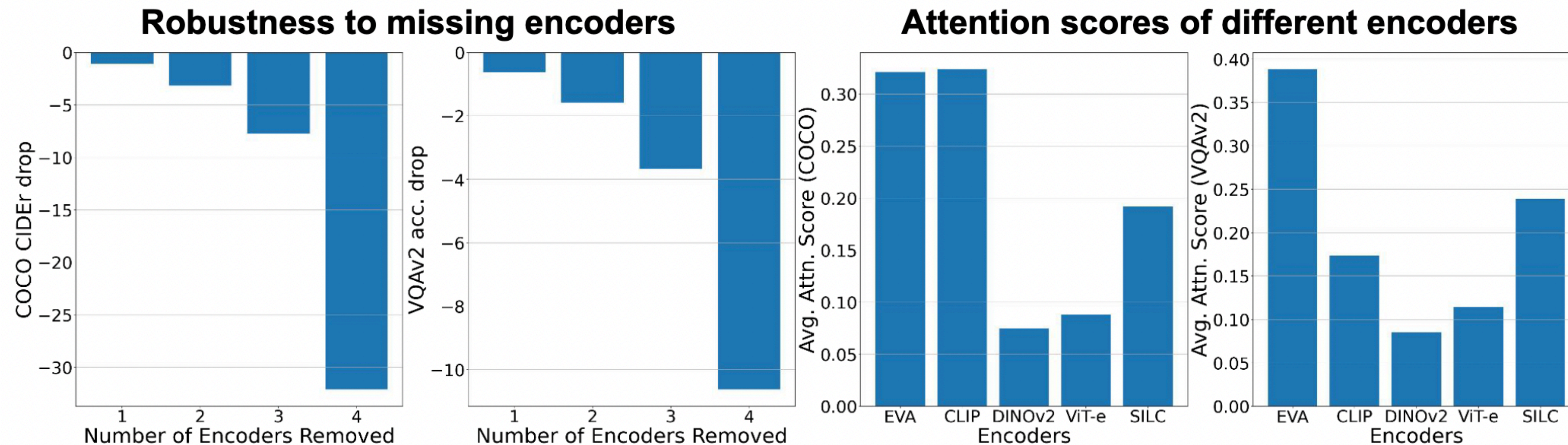
Method	# params		Fine-tuned			Zero-shot			
	Trainable	Total	VQAv2 test-dev	OKVQA val	GQA test-dev	VizWiz-QA test-dev	GQA test-dev	MMVP test	POPE test
SimVLM [91]	632M	632M	80.0	-	-	-	-	-	-
Flamingo [3]	10.2B	80B	82.0	57.8	-	31.6	-	-	-
MiniGPT-v2 [14]	7B	8B	-	57.8	60.1	<u>53.6</u>	-	-	-
GiT2 [87]	5.1B	5.1B	81.7	-	-	-	-	-	-
Qwen-VL [6]	9.6B	9.6B	79.5	58.6	59.3	35.2	-	-	-
SPHINX-2k [61]	13B	16.5B	80.7	62.6	63.1	44.9	-	-	<u>87.2</u>
PaLI-17B [19]	16.9B	16.9B	84.3	<u>64.5</u>	-	-	-	-	-
BLIP-2 [56]	1.2B	12.1B	81.6	54.7	-	29.4	44.7	-	85.3
InstructBLIP [25]	188M	14.2B	-	55.5	-	33.4	<u>49.5</u>	16.7	78.9
ShareGPT4V [16]	13.4B	13.4B	81.0	-	64.8	-	-	-	-
LLaVA ^{1.5} [64]	13B	13.4B	80.0	-	63.3	<u>53.6</u>	-	24.7	85.9
LLaVA ^{1.6} [65]	13B	13.4B	-	46.3	<u>65.4</u>	-	-	-	86.3
LLaVA ^{1.5} (I-MoF) [84]	13B	13.6B	79.3	-	-	-	-	31.3	86.7
BRAVE 🦁	3B	10.3B	<u>82.5</u>	66.0	66.3	54.2	52.7	42.0	87.6

Quantitative results – VQA

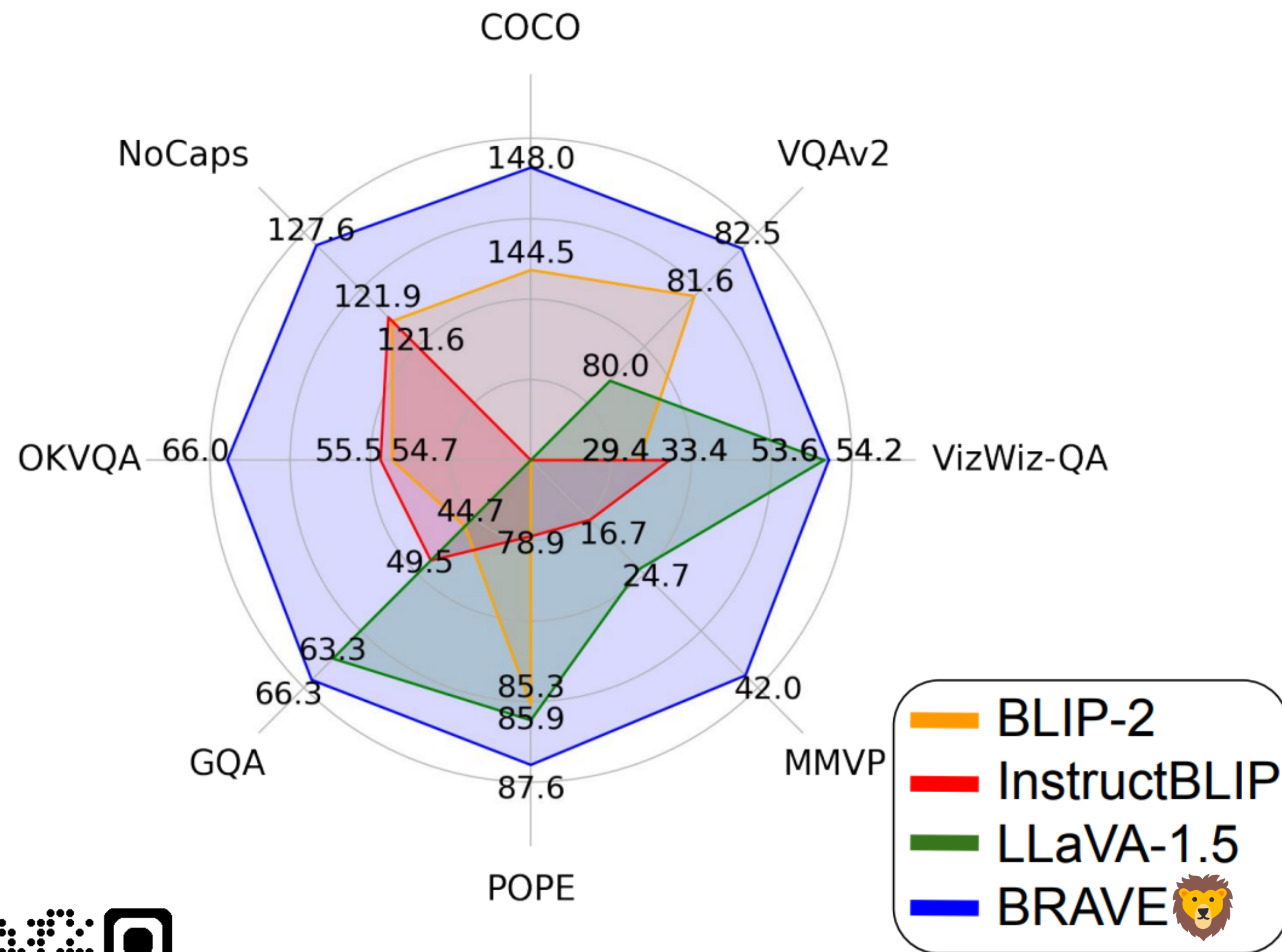
Method	# params		Fine-tuned			Zero-shot			
	Trainable	Total	VQAv2 test-dev	OKVQA val	GQA test-dev	VizWiz-QA test-dev	GQA test-dev	MMVP test	POPE test
SimVLM [91]	632M	632M	80.0	-	-	-	-	-	-
Flamingo [3]	10.2B	80B	82.0	57.8	-	31.6	-	-	-
MiniGPT-v2 [14]	7B	8B	-	57.8	60.1	<u>53.6</u>	-	-	-
GiT2 [87]	5.1B	5.1B	81.7	-	-	-	-	-	-
Qwen-VL [6]	9.6B	9.6B	79.5	58.6	59.3	35.2	-	-	-
SPHINX-2k [61]	13B	16.5B	80.7	62.6	63.1	44.9	-	-	<u>87.2</u>
PaLI-17B [19]	16.9B	16.9B	84.3	<u>64.5</u>	-	-	-	-	-
BLIP-2 [56]	1.2B	12.1B	81.6	54.7	-	29.4	44.7	-	85.3
InstructBLIP [25]	188M	14.2B	-	55.5	-	33.4	<u>49.5</u>	16.7	78.9
ShareGPT4V [16]	13.4B	13.4B	81.0	-	64.8	-	-	-	-
LLaVA ^{1.5} [64]	13B	13.4B	80.0	-	63.3	<u>53.6</u>	-	24.7	85.9
LLaVA ^{1.6} [65]	13B	13.4B	-	46.3	<u>65.4</u>	-	-	-	86.3
LLaVA ^{1.5} (I-MoF) [84]	13B	13.6B	79.3	-	-	-	-	31.3	86.7
BRAVE 	3B	10.3B	<u>82.5</u>	66.0	66.3	54.2	52.7	42.0	87.6

More results & analysis

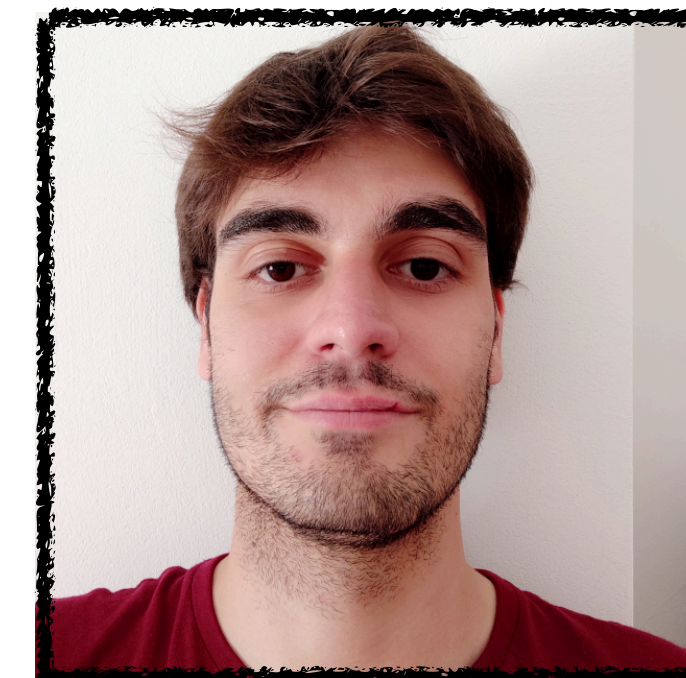
- Qualitative results on captioning and VQA
- Ablations of design choices (training data, fine-tuning, LLM, etc.)
- Contribution of different vision encoders



BRAVE🦁: Broadening the visual encoding of vision-language models



Oğuzhan Fatih Kar



Alessio Tonioni



Petra Poklukar



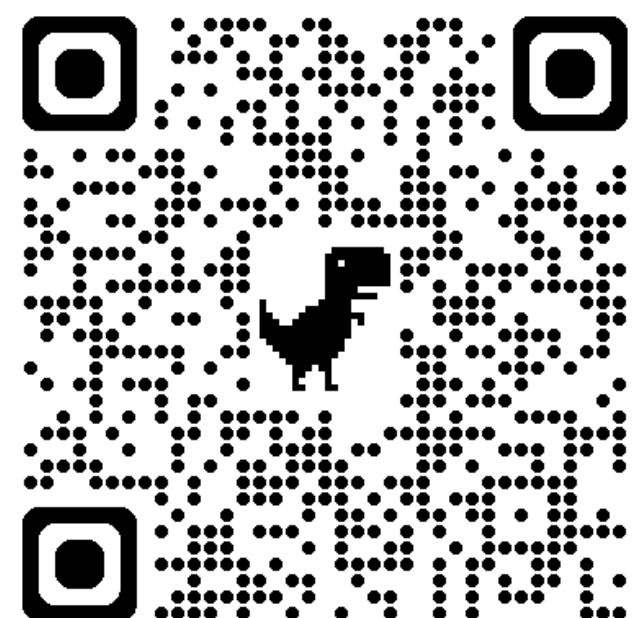
Achin Kulshrestha



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